Long-Term Mental Health Effects of Schooling in Developing Countries: New Causal Evidence for Brazil, China, India, and Mexico

Abstract

Policies to increase schooling attainment may be an effective long-term strategy to tackle later-life mental health problems given robust associations between more schooling and better older-age mental health. However, evidence on the causal relationship in developing countries is scant. We contribute by conducting cross-country comparative analysis for the causal effects of schooling on mental health of older adults in four diverse developing countries—Brazil, China, India, and Mexico—using harmonized data and a nonparametric partial-identification approach that bounds the causal effects. We document important effects at the lower part of the schooling distribution. An extra year of schooling reduces the probability of likely being depressed by 0 to 3.3% in Brazil, 0.3 to 5.5% in China, 1.1 to 3.8% in India, and 0.6 to 6.2% in Mexico when going from having none to completing primary schooling.

JEL Classification: I10, I26, J14

Keywords: Mental Health; Aging; Partial-Identification; Bounds; Schooling

1. Introduction

Can schooling protect against poor mental health decades later in life? This is a vital question for policy makers in developing countries because of the increasing pace of population aging. It is projected that by 2050, 79% of the world's population aged 60+ years will be living in developing countries (United Nations 2017). Mental health problems are also highly prevalent among older adults in developing countries, with a systematic review and meta-analysis (Zenebe et al. 2021) estimating the prevalence of depression among older adults to be 41%. Mental health conditions are among the leading causes of morbidity and mortality worldwide. The 2019 Global Burden of Disease, Injuries, and Risk Factor Study (GBD 2020) reported that mental disorders accounted for 125.3 million disability adjusted life years (DALYS), representing five percent of global DALYS and ranked as the seventh leading cause. Given aging populations, it is thus vital to identify interventions to improve mental health at older ages in developing countries.

Policies to increase schooling attainment may be an effective long-term prevention strategy, since more schooling is associated with better mental health at older ages in both developing (Brinda et a. 2016; Kasa et al. 2022; Srivastava et al. 2021; Zhao et al. 2024) and developed countries (Chlapecka et al. 2023; Domènech-Abella et al. 2018; Zivin et al. 2010). Several explanations exist for this relationship. In the Grossman (1972) model of health production, schooling can improve health by increasing the efficiency to produce more health from given inputs and the allocative efficiency through selecting inputs for better health production. Mental health can be viewed as a component of overall health, which is increased through schooling affecting productive and allocative efficiency. Schooling is associated with better physical health (Johnson et al. 2010), which could in turn improve mental health since declining physical health is correlated with worsen mental health (Ohrenberger et al. 2017). Improvements

in mental health could arise through schooling increasing income and reducing the likelihood of poverty. Poverty can further worsen mental distress from low income, since it exposes individuals to other risk factors such as violence that also impact mental health. Individuals with higher schooling attainment tend to have larger social networks and better access to social support to help deal with psychological problems. While there are multiple channels through which schooling benefits mental health, there may be other channels leading to a negative effect of schooling. For example, schooling could worsen mental health if it is associated with greater alcohol consumption, or if more-schooled individuals work in high-paced stressful environments. Nevertheless, schooling is viewed by some as a fundamental cause of better health because of the perception that schooling embodies access to important resources and affects multiple health outcomes through several mechanisms (Link & Phlean 1995).

An open question is whether the relationship between schooling and older-age mental health is causal. Reported associations may be non-causal due to omitted variable bias from unobserved third factors that are correlated with schooling and mental health. Most of the causal evidence in the literature is for older adults in developed countries, coming from studies employing (1) instrumental variable (IV) designs exploiting changes in compulsory schooling laws and (2) within-sibling comparisons. Studies have found evidence for null and protective effects. Hamad et al. (2019) found a small statistically insignificant effect of 1.4 percentage point reduction in the probability of depression (based on an 8-item Center for Epidemiological Studies Depression Scale) for an extra year of schooling for older adults (average age of 76 years) in the US Health & Retirement Study (HRS) using variation in state-level compulsory schooling laws. Based on identical twins with an average age of 54 years from the Virgina Twin Registry, Halpern-Manners et al. (2016) found an additional year of schooling decreased their depression scale (derived from

a 30-item subset of the 90-item Symptom Checklist) by 0.05 standard deviations but was statistically insignificant. Using data on older adults in the Survey of Health, Ageing and Retirement in Europe and changes in compulsory schooling laws across several European countries, Crespo (2014) found an extra year of schooling reduced the probability of depression (measured using the EURO-D 12-item scale) by 30%. Using the same dataset and approach but different survey years and countries, Mazzonna (2014) found a 15% reduction in the likelihood of depression, and that the protective effects were only for men.

Two studies provide evidence indicating that more schooling could worsen older-age mental health. Dahman & Schnitzlein (2019) examined the relationship between schooling and mental health for individuals aged 50-85 years in the German Socio-Economic Panel using the increase in the required years of compulsory schooling from eight to nine that occurred in West Germany between 1949-1969. They found an extra year of schooling increased the risk of developing a mental disorder (based on the mental component summary score) by 4.7 percentage points, but the estimate was statistically insignificant. Using the increase in school-leaving age from 15 to 16 in the UK, Avendano et al. (2020) found an extra year of schooling increased the probability of self-reported depression/anxiety by 30% for older adults (average age of 54 years) in the Annual Population Survey. They argue this was due to the schooling reform forcing young people who did not want to stay in school, but rather go to the labor market, to continue their schooling. These young people may have been negatively affected by being forced to stay in a stressful academic environment in which they were less likely to succeed compared to their peers.

However, the negative effects of schooling have not been reported in other UK studies. Using the UK Biobank, Amin et al. (2023) found protective effects of schooling on the mental health (measured with the recently validated 4-item recent depressive symptom) of older adults

(average age of 57 years) in the UK Biobank using sibling fixed-effects regressions with genetic controls. Van de Weijer et al. (2024) found no causal effects on the probabilities of having depression, anxiety, or manic or bipolar disorder (measured based on medical records and self-reports) across three different research designs (changes in compulsory schooling laws, sibling fixed-effects, and Mendelian Randomization) in the UK Biobank. The mixed findings for the UK and in the wider literature on developed countries could be due to different mental health measures and methods being employed.

Evidence on the causal relationship between schooling and older-age mental health in developing countries is sparse. To our best knowledge Hu (2024) is the only study that has estimated schooling effects on later-life mental health for a developing country. Using the China Health and Retirement Longitudinal Study and the cultural revolution as a natural experiment—which disrupted access to schooling—she found no effect of schooling on mental health (measured with a 10-item Center for Epidemiological Studies Depression Scale) for rural women.

There is some evidence that more schooling improves mental health at middle ages in developing countries. Using the China Family Panel Study and the 1986 compulsory schooling law for identification Wang (2021) found an extra year of schooling improved the 6-item Kessler psychological distress scale by 0.14 standard deviations. Using the same dataset and schooling reform but with a regression-discontinuity kink design, Jiang et al. (2020) found a reduction of 0.09 standard deviations in the 10-item Kessler scale and a 5 percentage point decrease in the probability of depression per extra year of schooling. Using a sample of Chinese middle-aged twins, Behrman et al. (2015) found an improvement of 0.04 standard deviations in the mental

health scale per extra year of schooling in their twins fixed-effects regressions.[1] Using schooling reforms in 1980 in Zimbabwe, Kondirolli & Sunder (2021) found an extra year of schooling reduced the probability of reporting symptoms related to depression by 11%. Whether findings for middle-ages are generalizable for long-term effects at older ages depends on the rate of depreciation of mental health (Kaestner et al. 2020).[2]

We contribute by conducting a cross-country comparative analysis for the causal effects of schooling on the mental health of older adults in four diverse developing countries with harmonized data and a common econometric approach. We use aging datasets for Brazil, China, India, and Mexico, that are modeled after the HRS. We measure mental health with a binary indicator for the probability of likely being depressed based on country-specific cutoffs for the underlying Center for Epidemiological Studies Depression Scale and use the 2011 International Standard Classification of Education to harmonize schooling attainment. For causal inference, we employ a nonparametric partial-identification approach (Manski & Pepper 2000) that estimates bounds on population average treatment effects (ATE) of increasing schooling at different parts of schooling distributions. Hence, this approach allows for inference on effects for populations and schooling levels beyond those affected by compulsory schooling laws (unlike, for example, IV or

[1]Their mental health scale is based on the question "Do you have the following emotions: Sadness, Fear, Indignation, and Disgust? They sum up responses to these questions: often (1), occasionally (2), seldom (3), never (4).

[2]Kaestner et al. (2020) extend the Grossman (1972) model of health production and show the effect of schooling on health over the lifecycle depends on the rate of health depreciation. Their model predicts that schooling gradients in mental health will be larger at younger ages because depreciation of mental health is more pronounced at younger ages. Schooling effects on mental health at middle and older ages will thus differ depending on differences in mental health depreciation.

regression discontinuity approaches).[3] By using the same mental health and schooling measures along with a common research design we are better able to compare schooling effects across countries with varying development, institutional oversight, and cultures.

Our approach is rooted in the theory of causal inference based on counterfactuals (Imbens & Rubin 2015; Morgan & Winship 2014). The key assumptions in our approach are: (1) individuals with more schooling have on average lower latent probabilities of likely being depressed compared to individuals with less schooling and (2) more schooling does not increase the latent likelihood of depression for an individual. We then employ mothers' schooling as a "monotone instrumental variable"—a variable that is assumed to have a weakly mean decreasing relationship with latent depression probabilities—to help tighten the bounds.

We discuss the plausibility of our assumptions in section 3, but acknowledge here that our second assumption may be considered strong, as there are channels through which more schooling may worsen mental health. However, we argue that mental health is determined by many diverse factors related to social and economic contexts. The assumption does not rule out detrimental channels but instead assumes the positive effects of schooling through numerous other channels outweigh any possible negative effects. Similarly, the arguments in Avendano et al. (2020) would

[3]This partial-identification approach has been used in other contexts such as estimating causal effects of (i) parental education on children's education (De Hann 2011), (ii) education on older-age cognition (Amin et al. 2025) (iii) unemployment on mental health (Cygan-Rehm et al. 2017) and (iii) mental health on labor market outcomes (Germinario et al. 2022). While Amin et al. (2025) focus on older-age cognition in the U.S., they also examine education effects on mental health. To our best knowledge, this is the first time that the approach has been applied to examine education effects on mental health of older adults across several developing countries.

only violate this assumption if the negative "coercion" effects of compulsory schooling laws outweigh the positive schooling effects.

We find important effects at the lower part of the schooling distribution. An extra year of schooling reduces the probability of likely being depressed by 0 to 3.3% in Brazil, 0.3 to 5.5% in China, 1.1 to 3.8% in India, and 0.6 to 6.2% in Mexico when going from having no schooling to completing primary schooling, with the effects being statistically different from zero for China, India and Mexico. We provide evidence that the effects of completing primary schooling may be working through higher socioeconomic status. At this margin, we also find some suggestive evidence of differences by (1) gender for India and Mexico and (2) social identity in China (hukou status) and India (caste). At other schooling margins (e.g, increasing schooling from lower- to upper-secondary, or from upper- to post-secondary) we cannot statistically distinguish between null, small, moderate and potentially large effects.

2. Data

2.1 Description of Studies

We use data from the Brazilian Longitudinal Study of Aging (ELSI), China Health & Retirement Longitudinal Study (CHARLS), Longitudinal Aging Study in India (LASI) and Mexican Health and Aging Study (MHAS). These studies are part of the HRS family of surveys, which share common characteristics, such as being population representative of older adults and having coordinated survey instruments.[4] Key aspects of the studies are summarized in Table 1

[4] HRS style data is also available for South Africa (Health and Aging in Africa: A Longitudinal Study of an INDEPTH Community in South Africa) and Costa Rica (The Costa Rican Longevity and Healthy Aging Study). We do not include

panel A. CHARLS and LASI survey older adults aged 45+ years, whereas ELSI and MHAS survey adults aged 50+ years. In CHARLS and MHAS only one age-eligible individual from the household is interviewed, while all age-eligible household individuals are interviewed in ELSI and LASI. Spouses are interviewed in all studies. There is no age requirement for the spouses to be interviewed in CHARLS, LASI, and MHAS. In ELSI, spouses are only interviewed if they are 50+ years old.

2.2 Mental Health and Schooling Measures

Mental health is measured using the Center for Epidemiological Studies Depression Scale (CES-D)—a widely used self-reported questionnaire to measure depressive symptoms—in all four studies. The original CES-D scale consist of 20 questions asking people to report their frequency of feelings to statements such as "I was bothered by things that usually don't bother me", "I felt depressed" in the past week. The studies employed modified versions of the CES-D scale (Table 1 panel B), with eight questions asked in ELSI, nine in MHAS, and ten in CHARLS and LASI. In CHARLS participants respond to these questions on a four-point scale (rarely or none of the time; some or little of the time; occasionally or a moderate amount of time; most or all of the time) whereas in the other studies responses are binary (yes/no). To compare across studies, we follow Banerjee et al. (2023) and measure mental health with an indicator for the probability of likely being depressed which is based on country-specific cutoffs obtained from Steffick et al. (2000) for Brazil and India, Chen & Fang (2020) for China, and Torres & Wong (2013) for Mexico.

South Africa and Costa Rica in our analysis as their surveys do not contain information on mothers' schooling which we use as a monotone instrumental variable.

Schooling systems differ by country, and in each dataset respondents report their highest schooling attainment with scales using country-specific responses. We follow Zhang et al. (2024) and use the 2011 International Standard Classification of Education to cross-walk and harmonize schooling into categories for: (a) less than primary; (b) primary; (c) lower secondary; (d) upper secondary; and (e) post-secondary (Table 1 panel C). Our departure from Zhang et al. (2024) is that we split less than primary into no schooling and some primary schooling in order to identify causal effects of increasing schooling along the policy-relevant margin of moving from none to primary.

As part of our econometric approach, we employ mother's schooling as a monotone instrumental variable (we define this concept in the next section). Possible responses for mother's highest schooling attainment are shown in Table 1 panel D. We harmonize mothers' schooling with dummy variables for no schooling, some primary, and primary or higher.

2.3 Analytical Sample and Descriptive Statistics

Appendix figure A1 provides a flowchart to illustrate how we arrive at our analytical sample. We use the RAND versions of the aging datasets and limit the analysis to individuals (both participants and spouses) aged 50+ years in the first wave of surveys.[5] We then exclude individuals with missing data on age (only in CHARLS), schooling, mental health, and mother's schooling. Final sample sizes are 7,595 for Brazil, 12,191 for China, 49,538 for India, and 11,248 for Mexico.

Summary statistics are shown in Table 2. The average age is around 62-63 years, with the largest group being individuals between 50-59 years of age. Over half the participants are female.

[5] The RAND versions are cleaned, harmonized versions of the aging studies that are available from the Gateway to Aging for all countries apart from Brazil. For Brazil, we use the original dataset available from the ELSI study website.

Schooling attainment is lowest in India, with 49% of older adults having never been to school, and highest in Brazil where only 12% of older adults have no schooling. Despite having the lowest schooling attainment, older adults in India comparatively have better mental health with 26% of older adults classified as likely being depressed. The highest probability of likely being depressed is in China (39%). The distribution of mothers' schooling is similar for the Latin-American and the Asian countries. In Brazil and Mexico, about 55% of the participants' mothers have/had no schooling, whereas in China and India it is about 90%. Gender-stratified summary statistics are provided in Table 3. Men have more schooling on average than women. The largest gender-schooling gaps are in China and India, where men have almost twice the amount of schooling as women. In China, women have a substantially higher probability of likely being depressed (46%) compared to men (32%). The gender disparity is much smaller in India with 28% of women likely to be depressed compared to 24% of men. While gender disparities in schooling are much smaller in Brazil and Mexico, women are almost twice as likely to be depressed than men in both countries.

3. Partial-Identification Approach

To explain our approach for causal inference let $Y_i\,(t_1)$ and $Y_i(t_2)$ be two potential outcomes, i.e., the probability that individual i is likely depressed as functions of two schooling levels (e.g. primary schooling t_2, no schooling t_1). We are interested in the population ATE of increasing schooling from none to primary on the probability of likely being depressed:

(1): $\Delta\,(t_1, t_2) \equiv E[Y(t_2)] - E[Y(t_1)]$.

ATE estimation is complicated because the potential outcome $Y(t_2)$ is unobserved for individuals with realized schooling level different from t_2, and the potential outcome $Y(t_1)$ is unobserved for individuals with realized schooling level different from t_1. Letting S denote realized schooling, the expected potential outcome $E[Y(t_2)]$ is:

$$(2)\ E[Y(t_2)] = E[Y(t_2)|S < t_2] * P(S < t_2) + E[Y(t_2)|S = t_2] * P(S = t_2) + E[Y(t_2)|S > t_2] * P(S > t_2).$$

The data identify the sample analogues of all the right-side quantities except of the counterfactuals $E[Y(t_2)|S < t_2]$ and $E[Y(t_2)|S > t_2]$. A similar equation applies to $E[Y(t_1)]$. The partial-identification approach we employ makes assumptions to bound each of the counterfactuals in the expressions for $E[Y(t_1)]$ and $E[Y(t_2)]$ to then bound the ATE. The assumptions we employ are explained below and most of their implied bounds are illustrated in Figure 1:

Assumption 1: Bounded Support: Manski (1989) suggested a bounded support assumption, whereby one imposes minimum (Y_{min}) and maximum (Y_{max}) values for the outcome variable. This is an innocuous assumption in our case, as the depression indicator has $Y_{min} = 0$ and $Y_{max} = 1$. Once Y_{min} and Y_{max} are appropriately substituted for the missing counterfactuals, this gives Manski's (1989) "no-assumption (NA)" bounds, which for $E[Y(t_2)]$ are:

$$(3)\ E[Y|S = t_2] * P(S = t_2) \leq E[Y(t_2)] \leq P(S < t_2) + E[Y|S = t_2] * P(S = t_2) + P(S > t_2)$$

A similar expression can be derived for $E[Y(t_1)]$. NA bounds are typically wide, and contain zero by construction. To tighten the bounds, we employ three monotonicity assumptions introduced in Manski (1997) and Manski and Pepper (2000): (a) monotone treatment selection; (b) monotone treatment response; and (c) monotone instrumental variable.

Assumption 2: Monotone Treatment Selection (MTS): MTS assumes that individuals with more realized schooling on average have weakly lower potential depression probabilities at every schooling level t. Formally, for two schooling levels μ_1 and μ_2 with $\mu_2 \geq \mu_1$ MTS assumes $E[Y(t)|S = \mu_2] \leq E[Y(t)|S = \mu_1]$. For example, MTS requires that the expected value of the potential depression indicator at any schooling level t of individuals with primary schooling be less than or equal to that of individuals with no schooling.

MTS is untestable since most potential outcomes are counterfactual, though we believe it is highly plausible. Economic models of human capital posit that individuals with higher innate ability have more schooling (Ben-Porath 1967), and numerous studies have found that intelligence/cognition test scores predict fewer mental health problems and lower likelihood of developing mental disorders (Gale et al. 2010; Konen et al. 2009; Mortensen et al. 2005; Nordmo et al. 2024; Wraw et al. 2016). More generally, MTS captures the notion that individuals who self-select into higher schooling levels are more likely to have pre-treatment characteristics (e.g., higher intelligence, better health inputs and family background) that also make them more likely to have lower expected potential depression probability at any given schooling level, relative to individuals who self-select into lower schooling levels. Appendix Table A1 provides indirect support for this notion by showing that individuals with higher schooling attainment are less likely to have mothers with no schooling.

The MTS assumption would be violated if the expected value of the potential depression indicator is higher for more-schooled individuals. One possibility is that highly/gifted intelligent individuals are more prone to mental health problems (e.g., due to a heightened sensitivity to the environment). For instance, Karpinski et al. (2018) surveyed American Mensa members—individuals who scored above the 98th percentile on IQ tests—and found that among this group more individuals had self-reported mental disorders than expected given national averages. However, given that MTS is based on expected values, the proportion of such individuals would have to be extremely high to reverse the direction of the inequality in the MTS assumption.

Under MTS, the counterfactual $E[\,Y(t_2) \mid S < t_2\,]$, cannot be less than $E[\,Y(t_2) \mid S = t_2\,]$, which is point identified by the observed mean for those receiving schooling level t_2 ($E[Y|S = t_2]$). Similarly, MTS implies that $E[\,Y(t_2) \mid S > t_2\,]$ cannot be larger than $E[\,Y(t_2) \mid S = t_2\,] = E[Y|S = t_2]$. Then using equation (2), the MTS bounds on $E[Y(t_2)]$ are given by (Manski and Pepper, 2000):

$$(4)\ E[Y|S = t_2] * P(S < t_2)\ + E[Y|S = t_2] * P(S = t_2)$$
$$\leq E[Y(t_2)] \leq$$
$$P(S < t_2) + \ E[Y|S = t_2] * P(S = t_2) + \ E[Y|S = t_2] * P(S > t_2)$$

A similar expression can be derived for $E[Y(t_1)]$.

Assumption 3: Monotone Treatment Response (MTR): MTR assumes that more schooling does not increase the probability of likely being depressed for any individual; that is, for two schooling levels t_1 and t_2 with $t_2 > t_1$, $Y_i(t_2) \leq Y_i(t_1)$ for all i. For instance, MTR compares the potential depression indicator under primary schooling versus the potential depression indicator under no

schooling for the same individual. MTR is thus an assumption about the (weak) ranking of the potential outcomes for the same individual. This is different from the MTS assumption, which compares the expected value of the potential outcome under the same schooling level (e.g., primary schooling) for two different subpopulations defined by their observed schooling levels (e.g., primary versus no schooling).

MTR is a stronger assumption than MTS as it must hold for all individuals (rather than just on average) and there are channels through which schooling may increase the probability of depression. For example, more schooling could increase the potential likelihood of depression if it leads an individual to consume more alcohol or work in a stressful environment compared to the case in which this individual had acquired with less schooling. However, mental health for an individual is determined by multiple diverse factors related to social and economic contexts. MTR does not rule out these potentially detrimental channels, but rather assumes that the positive channels linking schooling to better mental health dominate for every individual.

A key implication from MTR is that $E[Y(t_2)|S = t_\ell] \leq E[Y(t_1)|S = t_\ell]$ for any ℓ, given that $t_2 > t_1$. This means, for example, that the counterfactual $E[Y(t_2)|S = t_1]$ is no greater than $E[Y(t_1)|S = t_1] = E[Y|S = t_1]$, thus decreasing the NA upper bound on $E[Y(t_2)|S = t_1]$. By extending this idea to all realized schooling levels below t_2, one obtains that the counterfactual $E[\,Y(t_2) \mid S < t_2\,]$ in equation (2) cannot be greater than $E[\,Y \mid S < t_2\,]$. Moreover, by applying an analogous argument when considering all realized schooling levels above t_2, one obtains that the counterfactual $E[\,Y(t_2) \mid S > t_2\,]$ cannot be less than $E[\,Y \mid S > t_2\,]$. Using equation (2), the MTR bounds on $E[Y(t_2)]$ are given by (Manski, 1997):

$$(5)\ E[Y|S=t_2]*P(S=t_2)+E[Y|S>t_2]*P(S>t_2)$$
$$\leq E[Y(t_2)] \leq$$
$$E[Y|S<t_2]*P(S<t_2)+\ E[Y|S=t_2]*P(S=t_2)+\ P(S>t_2)$$

As before, a similar expression can be derived for $E[Y(t_1)]$.

Tighter bounds can be obtained by combing the MTS and MTR assumptions. The MTS+MTR bounds on $E[Y(t_2)]$ are:

$$(6)\ E[Y|S=t_2]*P(S<t_2)\ +E[Y|S=t_2]*P(S=t_2)+E[Y|S>t_2]*P(S>t_2)$$
$$\leq E[Y(t_2)] \leq$$
$$E[Y|S<t_2]*P(S<t_2)+\ E[Y|S=t_2]*P(S=t_2)+\ E[Y|S=t_2]*P(S>t_2)$$

A testable implication of the combined MTS+MTR assumptions is that observed average depression probabilities are weakly decreasing in schooling. If this testable implication does not hold, then at least one of these assumptions is not satisfied in the data, providing a check on them. Table 4 shows that the probability of likely being depressed is decreasing as a function of schooling. For individuals with no schooling the probability of likely being depression is 40% in Brazil, 49% in China, 30% in India and 46% in Mexico; in contrast for individuals with primary schooling it is 38% in Brazil, 36% in China, 24% in India, and 31% in Mexico. While this does not imply that the MTR+MTS assumptions jointly hold in the sample, it is consistent with their

testable implication. In other words, the data does not reject the implication—in terms of the observable data—that stems from the combination of the two assumptions.[6]

Assumption 4: Monotone Instrumental Variable (MIV): In spite of its name, an MIV is not a conventional IV. In the IV framework, where instruments are used to address endogeneity, a valid instrument is a variable that is related to treatment and satisfies that the instrument affects the outcome only through treatment (the exclusion restriction).

In the partial-identification framework we use, MIVs do *not* need to be related to the treatment or satisfy the exclusion restriction. Rather, an MIV is a variable with a weakly monotone (increasing or decreasing) mean relationship with potential outcomes $Y(t)$, and it is used to tighten bounds derived under other assumptions. Therefore, its requirement is fairly mild. Specifically, taking the case of a weakly decreasing MIV denoted by Z, it satisfies the following for all schooling levels t:

$$(7) \quad m_1 \leq m \leq m_2 \;\Rightarrow\; E[Y(t)|Z = m_1] \geq E[Y(t)|Z = m] \geq E[Y(t)|Z = m_2]$$

[6] In the full sample for Brazil the probability of depression for individuals with primary schooling (0.38) is slighlty higher than for individuals with some primary (0.37). The difference is not statistically significantly different from zero and thus is still consistent with the MTS+MTR assumption. The only case where there is evidence to suggest the MTS+MTR assumption does not hold is when comparing women with post-secondary schooling to women with upper-secondary schooling in Mexico. In this case, the probability of likely being depressed with post-secondary schooling (0.24) is statistically significantly higher than the probability of likely being depressed with upper-secondary schooling (0.18). This must be kept in mind when interpreting the results for these groups in Mexico.

We use mothers' schooling as the MIV as it is empirically associated with better children's mental health in childhood, adolescence, and adulthood (Fakhrunnisak & Patria 2022; Graeber & Schnitzlein 2019; Huges et al. 2024; Meyrose et al. 2018; Quesnel-Vallée & Taylor 2012; Sonego et al. 2013). Mothers' schooling could improve children's health through spousal schooling, better labor market opportunities increasing resources available to invest in children, increase children's schooling, greater access to information and health knowledge, and better health care utilization. These channels are allowed by the MIV assumption and help to justify its plausibility. This assumption does not require the MIV to have causal effects on outcomes.

The MIV assumption implies that if we take two subsamples where individuals counterfactually have the same level of schooling but two different levels of mothers' schooling (e.g., mothers with no schooling m_1 and mothers with primary schooling m_2), expected potential depression $E[Y(t)]$ will be weakly lower for the sample whose mothers completed primary schooling. The MIV assumption would be violated if the inequality flipped so that $E[Y(t)]$ for individuals whose mother's completed primary schooling is *higher* compared to $E[Y(t)]$ for individuals with mothers who had no schooling. It is possible that higher mothers' schooling worsens children's mental health. For example, there could be a detrimental effect on children's mental health if more schooled mothers have long working hours and are absent from home. However, the MIV assumption refers to average (rather than individual) potential outcomes. Thus, the proportion of such individuals would have to be implausibly high to reverse the direction of the weakly monotonic *mean* relationship. Lastly, note that the inequality holds weakly, so it also allows for such means to be equal.

With an MIV, one then divides the sample into subsamples based on values of Z and obtains bounds for each subsample. For the bin where Z has a value of m, an MIV lower bound

(respectively upper bound) is obtained by taking the largest (smallest) lower (upper) bound over all bins where $Z \geq m$ ($Z \leq m$). This is illustrated in Figure 2 (based on De Hann 2011), which shows fictitious MTS+MTR upper and lower bounds in three bins of Z. In the subsample Z=2, the maximum lower bound is estimated over all subsamples with Z≥ 2. This is the lower bound at Z=3, so this becomes the new lower bound at Z=2. Likewise, we can obtain a new upper bound at Z=2 by taking the smallest upper bound over all bins where $Z \leq 2$. In Figure 2, the smallest upper bound over all values Z≤ 2 is the upper bound at Z=1. So, this becomes the new upper bound at Z=2. This type of bounding approach is known as intersection-bounds. The MTS+MTR+MIV bounds are then obtained by taking the weighted average over all the conditional-on-Z bounds.

Bounds on the ATE $\Delta\,(t_1, t_2)$: Bounds on the ATE of increasing schooling from t_1 to t_2 for a given set of assumptions are calculated by:

$$(8)\ LB\ E[Y(t_2)] - UB\ E[Y(t_1)] \leq \Delta\,(t_1, t_2) \leq UB\ E[Y(t_2)] - LB\ E[Y(t_1)]$$

where LB and UB denote lower and upper bounds. Under the MTR assumption the upper bound on $\Delta\,(t_1, t_2)$ is never above zero, because MTR rules out that more schooling increases depression probabilities. Bounds for other schooling margins (e.g. increasing schooling from primary to high-school) are computed analogously.

Estimation and Inference: We implement the methods using the user-written STATA command *mpclr* (Germinario et al. 2021).[7] Bounds are estimated by plugging in sample analogs for the expectations and probabilities in the corresponding expressions. Confidence intervals (CIs) on the population ATE are constructed using methods developed by Chernozhukov et al. (2013), which deal with biases arising from taking the minimum or maximum (intersections) over several candidate bounds with the MIV assumption (see the *mpclr* documentation for further details).

4. Results

4.1 Effects of Primary Schooling

Results are shown in Table 5. Ordinary least squares (OLS) estimates in panel A column 3, which are likely non-causal, show that individuals with some primary schooling have statistically significantly lower probabilities of likely being depressed compared to individuals with no schooling (except in Brazil). The largest gradient is in Mexico, where the probability of likely being depressed is 8.5 percentage points lower for individuals with some primary schooling compared to individuals with no schooling. Column 4 provides the NA bounds, which are wide and contain zero. Bounds under the MTS assumption in column 5 are considerably narrower, but do not rule out null, negative, and positive effects. Using the MTR assumption alone in column 6 mechanically restricts the upper bound to zero, as MTR rules out the possibility that more schooling increases the likelihood of depression. The combination of the MTS+MTR assumptions in column 7 leads to substantially tighter bounds. While the bounds do not exclude zero, they

[7] The *mpclr* documentation is available at:

https://drive.google.com/file/d/18oNEjMT2XIKEpp98cmVyrFY7kyJ7qDTD/view

indicate that increasing schooling from none to some primary reduces the probability of likely being depressed by *at most* 7 percentage points in Brazil, 12 percentage points in China, 6 percentage points in India, and 13 percentage points in Mexico. These translate into reductions (relative to the control mean) of 18% for Brazil, 24% for China, 20% for India, and 28% for Mexico. For this schooling margin, using mother's schooling as the MIV divided into 3 bins (no schooling, some primary schooling, and primary schooling or higher) does not lead to a further tightening of bounds in column 8.[8]

Results for effects of increasing schooling from (i) some primary to primary and (ii) none to primary are given in panels B and C. In both panels, tighter bounds are obtained by adding MTS, MTR, and MTS+MTR assumptions similar to panel A. However, in panels B and C, using mother's schooling as the MIV yields tighter bounds. In panel B, the MTS+MTR+MIV bounds do not exclude zero, but the lower bounds are smaller (in absolute value) compared to the corresponding lower bounds under the MTS+MTR assumptions. In panel C, the MTS+MTR+MIV bounds and their 95% CI exclude null effects for all countries apart from Brazil. The bounds indicate that increasing schooling from none to primary reduces the probability of likely being depressed by 0-20% in Brazil, 2-33% in China, 7-23% in India, and 4-37% in Mexico (all percentages relative to the corresponding control mean). Assuming a difference of six years of schooling between individuals with none and primary schooling, an extra year of schooling

[8] For Brazil, the lower bound adding the MIV assumption is below the lower bound of the MTS+MTR bounds. This results from the statistical correction necessary to obtain unbiased estimates of the bounds when using intersection bounds. For details on the implementation of the Chernozhukov et al. (2013) methodology, see the *mpclr* documentation.

reduces the probability of likely being depressed by 0-3.3% in Brazil, 0.3-5.5% in China, 1.1-3.8% in India, and 0.6-6.2% in Mexico.

4.2 Effects of Secondary Schooling

Figure 3 (results provided in Appendix Table A2) summarizes results for increasing schooling from primary to lower secondary (panel A), lower to upper secondary (panel B), upper to post secondary (panel C), and primary to upper secondary (panel D). For the first three schooling comparisons, the bounds are consistent with no, small, moderate, and large reductions in the risk of likely being depressed. For example, increasing schooling from lower to upper secondary (panel B)—which is likely similar to effects of compulsory schooling laws that target high-school completion—decreases the probability of likely being depressed by 0-21% in Brazil, 0-34% in China, 0-17% in India, and 0-52% in Mexico. These translate into effects of 0-5.3% in Brazil, 0-8.5% in China, 0-4.3% in India, and 0-13% in Mexico per extra year of schooling (assuming a difference of four years between lower and upper secondary education). Among the four countries, India has the narrowest bounds in panels A-C. In panel D, the estimated bounds indicate statistically significant effects that are relatively tight for China, showing that going from primary to upper secondary schooling reduces the probability of likely being depressed by 11-39% (8-44% based on the 95% CI). The bounds for Brazil and Mexico also exclude zero but their 95% CIs do not.

4.3 Effects of Schooling on Self-Reported Health and SES

Self-reported health is a strong predictor of mortality (Idler & Benjamini 1997) and is consistently associated with indicators of physical health such as cardiovascular disease (van der

Linde et al. 2013), body mass index (Altman et al. 2016), and inflammatory markers (Christian et al. 2011). Physical health is correlated with mental health, and more schooling is correlated with better self-reported health. Given these correlations, we investigate physical health (proxied by self-reported health) as a potential channel through which schooling can affect mental health, by estimating effects of increasing schooling on self-reported health. We measure self-reported health with a dummy variable for being in excellent or very good health.[9] Given that more schooling is correlated with better self-reported health we employ non-negative versions of the MTS and MTR assumptions and also assume that mothers' schooling has a weakly increasing relationship with the mean potential self-reported health.[10] Results are summarized in Figures 4 and reported in Appendix Table A3. Overall, there is no clear evidence that increases in schooling at the lower part of the schooling distribution improve self-reported health, as the bounds and 95% CIs all include zero. The one exception is that increasing education from none to primary (panel C) increases the probability of reporting excellent/very good health by 6-28% in India.

Higher SES is another mechanism through which schooling can affect mental health. We examine this channel by estimating schooling effects on log of household consumption per capita (calculated as the sum of yearly expenditure on food and non-food items divided by the number

[9] In China, India, and Mexico, the responses to the self-reported health question are the same ranging from 1=excellent to 5=poor. In Brazil, the possible responses are 1=very good or excellent, 2=good, 3=regular, 4=bad, 5=very bad. Self-reported health is measured at the same time (wave 1) as mental health.

[10] The MTS assumption now states that individuals with more schooling have on average weakly higher potential probabilities of being in excellent/very good health at every schooling level. The MTR assumption requires that more schooling does not decrease the probability of excellent/very good health for every individual. The MIV assumption states that the expected value of potential excellent/very good health indicator is not strictly decreasing in mother's schooling.

of people in the household).[11] This is a better measure than income for SES because income can be highly variable in developing countries. Results are shown in Figure 5 (also reported in Appendix Table A4), which provides clear evidence that increasing schooling from none to primary improves SES. The bounds indicate an increase in household consumption per capita of 0.4-6% in Brazil, 0.6-4% in China, 0.7-3% in India, and 0.7-7% in Mexico, with their 95% CIs also excluding zero. We regard these findings as suggestive that SES is a mediator of the beneficial effect of schooling on the probability of likely being depressed.

4.4 Heterogeneity Analysis

We first examine heterogeneity by gender. Figure 6 (results reported in Appendix Table A5) shows gender-stratified results for effects of primary schooling. There are no clear statistically significant differences by gender since the estimated bounds by gender in each of the countries overlap.[12] There is only some suggestive evidence of gender differences when moving from none to primary schooling (panel C). First, while the estimated bounds and their 95% CI contain zero for both men and women in China, they are both narrower for women. Second, in Mexico null effects are only statistically excluded for women, with bounds (95% CI) indicating a reduction of 4-30% (2-36%) in the probability of likely being depressed. Third, the bounds and 95% CI both exclude zero in India, but the width of the bounds is narrower for women (10-23%) than for men (4-25%). Results for effects of secondary education are shown in Appendix Figure A2 and

[11] Since more schooling is positively correlated with household consumption, we employ non-negative versions of the MTS, MTR, and MIV assumptions.

[12] In panel B bounds are not shown for men in Brazil as the cross. The estimated bounds are [0.01, 0.00] and the 95% CI is (-0.03, 0.00). See Appendix Table A6.

Appendix Table A6 and there are no clear gender differences. One interesting observation is that in China the estimated bounds for moving from primary to upper secondary education statistically exclude zero for men and women but are shorter for men.

We next examine differences by social identity—hukou status (household registration system) in China and caste in India. In China, each person is assigned a hukou (either rural or urban) based on place of birth and lineage. Rural hukou holders often have restricted access to better education, healthcare, job opportunities and housing. In India, caste, religion, and indigenous status greatly determine social privilege. At the bottom of the hierarchy are the Scheduled Tribes (indigenous people), Scheduled Castes (known as Dalits or "ex-untouchables") and other backward classes. Muslims are the largest religious minority in India and often face social marginalization. Upper-caste Hindus are at the top of the hierarchy. Results for effects of primary education by social identity (apart for upper-caste Hindus) are shown in Figure 7 and reported in Appendix Tables A7.[13] The bounds greatly overlap at all educational comparisons, but there is some suggestive evidence that going from no to primary education protects the mental health of the more disadvantaged groups. Specifically, in panel E for China, null effects are statistically ruled out only for rural hukou holders (although the estimated lower bound for urban hukou holders is considerably lower than for rural hukou holders). For India in panel F, the bounds statistically exclude zero for all groups apart from Muslims and for Hindus who report no/other caste. Results for effects of secondary education are shown in Appendix Figures A3 and A4 for China and India respectively, and reported in Appendix Table A8. The only instance where null

[13] The caste variable groups individuals into Scheduled Caste, Scheduled Tribe, Other Backward Class, and no caste or other caste. Instead of upper-caste Hindus, we report results for Hindus who report no/other caste.

effects are statistically ruled out is when going from primary to upper secondary education for both rural (8-34%) and urban (6-26%) hukou holders.

5. Conclusion

Understanding causal effects of schooling on mental health of older adults in developing countries is vital due to the rapid pace of population aging. Despite the importance of this research question, empirical evidence is sparse. This is partly due to the difficulty of isolating quasi-exogenous variation in schooling needed to identify causal effects. Rather than attempting to isolate quasi-exogenous schooling variation to point identify the causal effect, we employ a nonparametric partial-identification that bounds causal effects by making assumptions on the direction in which (a) individuals self-select into schooling and (b) schooling affects mental health. In addition to transparent assumptions, our approach has advantages of (1) estimating effects of increasing schooling throughout the schooling distribution, (2) providing bounds on the population average treatment effect (ATE), and (3) being relatively straightforward to implement in different datasets.

Applying this approach to the HRS sister dataset for Brazil, China, India, and Mexico, we did not find evidence of clear protective effects of schooling at upper parts of the schooling distribution. For example, an additional year of schooling decreases the probability of likely being depressed by 0-5.3% in Brazil, 0-8.5% in China, 0-4.3% in India, and 0-12.8% in Mexico when increasing schooling from lower to upper secondary. This margin is akin to effects of compulsory schooling laws that target high-school completion. Our lower bounds are in line with the evidence on null effects of schooling found (using changes in compulsory schooling laws for identification)

for older adults in developed countries. However, the estimated upper bounds indicate there could potentially be important protective.

However, we find important effects at the lower part of the education distribution. An extra year of education reduces the probability of likely being depressed by 0-3.3% in Brazil, 0.3-5.5% in China, 1.1-3.8% in India, and 0.6-6.2% in Mexico when going from having no schooling to primary schooling. Furthermore, increasing schooling from none to primary clearly improved household consumption per capita (our proxy for SES), but did not improve the probability of being in excellent/very good health (our proxy for physical health). We view this as suggestive evidence that SES is a mediator of the protective effects of schooling on older-age mental health.

A limitation of our approach is that it does not deal with possible biases arising from sample selection issues. For example, in constructing our analytical samples we lost observations due to missing data on mental health and mothers' schooling. Since our estimated upper and lower bounds rely primarily on estimated averages for subpopulations defined by schooling status, biases on these estimated averages resulting from missing data will translate into biases of the estimated (lower or upper) bounds. If those biases are such that the bounds are wider, then the true parameter of interest is still covered by the estimated bounds, but if those biases lead to narrower bounds, then the true parameter could lie outside of the estimated bounds. Another source of sample selection bias could come from life-expectancies, which are generally much lower in developing countries. Individuals who survived to the time of the survey in the aging studies may have unmeasured characteristics that promote survival and mental health. In principle, these sample selection challenges could be dealt with partial-identification techniques. However, it is likely that the resulting estimated bounds would be wide. Despite these limitations, to our best knowledge,

these are the first findings demonstrating long-term protective effects of primary schooling on the mental health of older adults in developing countries.

References

Amin, V., Fletcher, J. M., Lu, Q., & Song, J. (2023). Re-examining the relationship between education and adult mental health in the UK: A research note. *Economics of Education Review*, *93*, 102354.

Amin, V., Behrman, J. R., Fletcher, J. M., Flores, C. A., Flores-Lagunes, A., & Kohler, H. P. (2025). Does Schooling Improve Cognitive Abilities at Older Ages? Causal Evidence from Nonparametric Bounds. Forthcoming, *Demography*.

Avendano, M., De Coulon, A., & Nafilyan, V. (2020). Does longer compulsory schooling affect mental health? Evidence from a British reform. *Journal of Public Economics*, *183*, 104137.

Banerjee, A., Duflo, E., Grela, E., McKelway, M., Schilbach, F., Sharma, G., & Vaidyanathan, G. (2023). Depression and loneliness among the elderly in low-and middle-income countries. *Journal of Economic Perspectives*, *37*(2), 179-202.

Behrman, J. R., Xiong, Y., & Zhang, J. (2015). Cross-sectional schooling-health associations misrepresented causal schooling effects on adult health and health-related behaviors: Evidence from the Chinese Adults Twins Survey. *Social Science & Medicine*, *127*, 190-197.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *Journal of Political Economy*, *75*(4, Part 1), 352-365.

Brinda, E. M., Rajkumar, A. P., Attermann, J., Gerdtham, U. G., Enemark, U., & Jacob, K. S. (2016). Health, social, and economic variables associated with depression among older people in low and middle income countries: World Health Organization study on global AGEing and adult health. *The American Journal of Geriatric Psychiatry*, *24*(12), 1196-1208.

Chen, Y., & Fang, H. (2020). The state of mental health among the elderly chinese. NBER Working Paper 16690.

Chernozhukov, V., Lee, S., & Rosen, A. M. (2013). Intersection bounds: estimation and inference. *Econometrica*, *81*(2), 667-737.

Chlapecka, A., Wolfová, K., Fryčová, B., & Cermakova, P. (2023). Educational attainment and anxiety in middle-aged and older Europeans. *Scientific Reports*, *13*(1), 13314.

Crespo, L., López-Noval, B., & Mira, P. (2014). Compulsory schooling, education, depression and memory: New evidence from SHARELIFE. *Economics of Education Review*, *43*, 36-46.

Cygan-Rehm, K., Kuehnle, D., & Oberfichtner, M. (2017). Bounding the causal effect of unemployment on mental health: Nonparametric evidence from four countries. *Health Economics*, *26*(12), 1844-1861.

Dahmann, S. C., & Schnitzlein, D. D. (2019). No evidence for a protective effect of education on mental health. *Social Science & Medicine*, *241*, 112584.

De Haan, M. (2011). The effect of parents' schooling on child's schooling: a nonparametric bounds analysis. *Journal of Labor Economics*, *29*(4), 859-892

Domènech-Abella, J., Mundó, J., Leonardi, M., Chatterji, S., Tobiasz-Adamczyk, B., Koskinen, S., ... & Haro, J. M. (2018). The association between socioeconomic status and depression among older adults in Finland, Poland and Spain: A comparative cross-sectional study of distinct measures and pathways. *Journal of Affective Disorders*, *241*, 311-318.

Fakhrunnisak, D., & Patria, B. (2022). The positive effects of parents' education level on children's mental health in Indonesia: a result of longitudinal survey. *BMC Public Health*, *22*(1), 949.

Fulford, S. (2014). Returns to education in India. *World Development*, *59*, 434-450.

Gale, C. R., Batty, G. D., Tynelius, P., Deary, I. J., & Rasmussen, F. (2010). Intelligence in early adulthood and subsequent hospitalization for mental disorders. *Epidemiology*, *21*(1), 70-77.

G. B. D., & Ärnlöv, J. (2020). Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, *396*(10258), 1223-1249.

Germinario, G., Flores, C.A., & Flores-Lagunes, A. (2021). mpclr: A Stata command for bias-corrected estimation and valid inference for nonparametric bounds on treatment effects. Available at: https://drive.google.com/file/d/18oNEjMT2XIKEpp98cmVyrFY7kyJ7qDTD/view

Germinario, G., Amin, V., Flores, C. A., & Flores-Lagunes, A. (2022). What can we learn about the effect of mental health on labor market outcomes under weak assumptions? Evidence from the NLSY79. *Labour Economics*, *79*, 102258.

Graeber, D., & Schnitzlein, D. D. (2019). The effect of maternal education on offspring's mental health. SOEP papers on Multidisciplinary Panel Data Research No. 1028.

Grossman, M. (1972): On the concept of health capital and the demand for health. *Journal of Political Economy,* 80(2), 223–255.

Halpern-Manners, A., Schnabel, L., Hernandez, E. M., Silberg, J. L., & Eaves, L. J. (2016). The relationship between education and mental health: new evidence from a discordant twin study. *Social Forces*, *95*(1), 107-131.

Hamad, R., Nguyen, T. T., Bhattacharya, J., Glymour, M. M., & Rehkopf, D. H. (2019). Educational attainment and cardiovascular disease in the United States: a quasi-experimental instrumental variables analysis. *PLoS Medicine*, *16*(6), e1002834.

Hu, L. (2024). Late-Life Depression among Rural Women in China: Exploring the Role of Education and Other Risk Factors. Santa Monica, CA: RAND Corporation, 2024.

Hughes, A. M., Torvik, F. A., van Bergen, E., Hannigan, L. J., Corfield, E. C., Andreassen, O. A., ... & Havdahl, A. (2024). Parental education and children's depression, anxiety, and ADHD traits, a within-family study in MoBa. *npj Science of Learning*, *9*(1), 46.

Imbens, G. W., & Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge university press.

Jiang, W., Lu, Y., & Xie, H. (2020). Education and mental health: Evidence and mechanisms. *Journal of Economic Behavior & Organization*, *180*, 407-437.

Johnson, W., Kyvik, K. O., Mortensen, E. L., Skytthe, A., Batty, G. D., & Deary, I. J. (2010). Education reduces the effects of genetic susceptibilities to poor physical health. *International Journal of Epidemiology*, *39*(2), 406-414.

Kaestner, R., Schiman, C., & Ward, J. (2020). Education and health over the life cycle. *Economics of Education Review*, *76*, 101982.

Karpinski, R. I., Kolb, A. M. K., Tetreault, N. A., & Borowski, T. B. (2018). High intelligence: A risk factor for psychological and physiological overexcitabilities. *Intelligence*, *66*, 8-23.

Kasa, A. S., Lee, S. C., & Chang, H. C. (2022). Prevalence and factors associated with depression among older adults in the case of a low-income country, Ethiopia: a systematic review and meta-analysis. *BMC Psychiatry*, *22*(1), 675.

Koenen, K. C., Moffitt, T. E., Roberts, A. L., Martin, L. T., Kubzansky, L., Harrington, H., ... & Caspi, A. (2009). Childhood IQ and adult mental disorders: a test of the cognitive reserve hypothesis. *American Journal of Psychiatry*, *166*(1), 50-57.

Kondirolli, F., & Sunder, N. (2022). Mental health effects of education. *Health Economics*, *31*, 22-39.

Link, B. G., & Phelan, J. (1995). Social conditions as fundamental causes of disease. *Journal of Health and Social Behavior*, 80-94.

Manski, C. F. (1989). Anatomy of the selection problem. *Journal of Human Resources*, 343-360.

Manski, C. F. (1997). Monotone treatment response. *Econometrica*, 65, 1311-1334.

Manski, C. F., & Pepper, J. V. (2000). Monotone instrumental variables with an application to the returns to schooling. *Econometrica,* 68(July), 997-1010.

Mazzonna, F. (2014). The long lasting effects of education on old age health: evidence of gender differences. *Social Science & Medicine*, *101*, 129-138

Meyrose, A. K., Klasen, F., Otto, C., Gniewosz, G., Lampert, T., & Ravens-Sieberer, U. (2018). Benefits of maternal education for mental health trajectories across childhood and adolescence. *Social Science & Medicine*, *202*, 170-178.

Mortensen, E. L., Sørensen, H. J., Jensen, H. H., Reinisch, J. M., & Mednick, S. A. (2005). IQ and mental disorder in young men. *The British Journal of Psychiatry*, *187*(5), 407-415.

Morgan, S. L., & Winship, C. (2015). *Counterfactuals and causal inference*. Cambridge University Press.

Nordmo, M., Sunde, H. F., Kleppestø, T. H., Nordmo, M., Caspi, A., Moffitt, T. E., & Torvik, F. A (2024). Cognitive Abilities and Educational Attainment as Antecedents of Mental Disorders: A Total Population Study of Males. Working Paper.

Ohrnberger, J., Fichera, E., & Sutton, M. (2017). The dynamics of physical and mental health in the older population. *The Journal of the Economics of Ageing*, *9*, 52-62.

Quesnel-Vallée, A., & Taylor, M. (2012). Socioeconomic pathways to depressive symptoms in adulthood: evidence from the National Longitudinal Survey of Youth 1979. *Social Science & Medicine*, *74*(5), 734-743.

Sonego, M., Llácer, A., Galán, I., & Simón, F. (2013). The influence of parental education on child mental health in Spain. *Quality of Life Research*, *22*, 203-211.

Srivastava, S., Purkayastha, N., Chaurasia, H., & Muhammad, T. (2021). Socioeconomic inequality in psychological distress among older adults in India: a decomposition analysis. *BMC Psychiatry*, *21*, 1-15.

Steffick, D. E., Wallace, R.B., Herzog, A.R., et al. (2000). Documentation of affective functioning measures in the health and retirement study. Ann Arbor, MI: University of Michigan, 15.

Torres, J. M., & Wong, R. (2013). Childhood poverty and depressive symptoms for older adults in Mexico: a life-course analysis. *Journal of Cross-Cultural Gerontology*, *28*, 317-337.

United Nations, Department of Economic and Social Affairs, Population Division (2017). World Population Ageing 2017 - Highlights (ST/ESA/SER.A/397).

Wang, T. (2022). The impact of education on mental health: evidence from compulsory education law in China. *Applied Economics Letters*, *29*(16), 1515-1521.

van de Weijer, M. P., Demange, P. A., Pelt, D. H., Bartels, M., & Nivard, M. G. (2024). Disentangling potential causal effects of educational duration on well-being, and mental and physical health outcomes. *Psychological Medicine*, *54*(7), 1403-1418.

Wraw, C., Deary, I. J., Der, G., & Gale, C. R. (2016). Intelligence in youth and mental health at age 50. *Intelligence*, *58*, 69-79.

Zenebe, Y., Akele, B., W/Selassie, M., & Necho, M. (2021). Prevalence and determinants of depression among old age: a systematic review and meta-analysis. *Annals of General Psychiatry*, *20*(1), 55.

Zhang, Y. S., O'Shea, B., Yu, X., Cho, T. C., Zhang, K. P., Kler, J., ... & Kobayashi, L. C. (2024). Educational Attainment and Later-Life Cognitive Function in High-and Middle-Income Countries: Evidence From the Harmonized Cognitive Assessment Protocol. *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, *79*(5), gbae005.

Zhao, R., Wang, J., Lou, J., Liu, M., Deng, J., Huang, D., & Fang, H. (2024). The effect of education level on depressive symptoms in Chinese older adults–parallel mediating effects of economic security level and subjective memory ability. *BMC Geriatrics*, *24*(1), 635.

Zivin, K., Llewellyn, D. J., Lang, I. A., Vijan, S., Kabeto, M. U., Miller, E. M., & Langa, K. M. (2010). Depression among older adults in the United States and England. *The American Journal of Geriatric Psychiatry*, *18*(11), 1036-1044.

Table 1: Data Summary

Country (Dataset)	Brazil (ELSI)	China (CHARLS)	India (LASI)	Mexico (MHAS)
A: Key Data Elements:				
Age Eligibility	≥50 years	≥45 years	≥45 years	≥50 years
People Interviewed per household	All age-eligible individuals; plus spouse if any	One age-eligible person; plus spouse if any	All age-eligible individuals; plus spouse if any	One age-eligible person; plus spouse if any
Spousal Inclusion	Only if age-eligible	Spouse of any age	Spouse of any age	Spouse of any age
Wave 1 Year	2015	2011	2017	2011
Wave 1 Sample Size	9,412 individuals from 8,285 households	17,708 individuals from 10,257 households	72,262 individuals from 43,364 households	15,186 individuals from 9,862 households
B: Mental Health:				
Mental Health Scale	CES-D	CES-D	CES-D	CES-D
Number of Questions	8	10	10	9
Question Responses[a]	Binary (yes/no)	4-point scale	Binary (yes/no)	Binary (yes/no)
Scale Range	0-8	0-30	0-10	0-9
Depression Cutoff	4	10	4	5
C: Schooling Attainment[b]				
None	Never studied	No formal education (illiterate)	Never attended school	0 years of education
Some primary	1st grade (elementary school); 2nd grade; 3rd grade; 4th grade	Did not finish primary school	Less than primary (standard 1-4)	1-5 years of education
Primary	5th grade	Sishu/home school; Elementary school	Primary school (standard 5-7)	6 years of education
Lower secondary	6th grade (middle school); 7th grade; 8th grade	Middle school	Middle school (standard 8-9)	7-9 years of education
Upper secondary	9th grade (high school); 10th grade; 11th/12th grade; GED	High School	Higher secondary (standard 12)	10-12 years of education
≥Post-secondary	Some college (incomplete); College complete; Specialization/medical residency; Masters degree; Doctoral degree/Phd	Vocational school; Two/Three year college/Associates degree; Four year college/Bachelor's	Diploma or certificate; Graduate degree (ba,bs); Post-graduate degree (ma,ms, phd); Professional course/degree (mbbs, mb,md)	≥13 years of education

		degree; Post-graduate (masters/Phd)		
D: Mothers' Schooling				
	Does/did not know how to read Has/had not completed elementary school Has/had completed elementary school Has/had completed middle school Has/had completed high school Has/had college degree	No formal education (illiterate) Did not finish primary school Sishu/home school; Elementary school Middle school High School Vocational school Two/Three year college/Associates degree; Four year college/Bachelor's degree Post-graduate (masters/Phd)	Never attended school Less than primary Primary school Middle school Higher secondary Diploma or certificate Graduate degree Post-graduate degree Professional course/degree	None Some Primary Primary More than primary

Notes: ELSI: Brazilian Longitudinal Study of Aging; CHARLS: China Health and Retirement Longitudinal; LASI: Longitudinal Aging Study in India; MHAS: Mexican Health & Aging Study. a: the response options are CHARLS are: rarely or none of the time (assigned 0); some or little of the time 1-2 days (assigned 1); occasionally or a moderate amount of the time 3 days (assigned 2); most or all of the time 5-7 days (assigned 3)

Table 2: Summary Statistics

	Brazil	China	India	Mexico
Demographics				
Age	61.63 (9.09)	62.11 (8.31)	62.77 (9.26)	61.83 (9.31)
Age Group				
50-59 years	0.50 (0.50)	0.46 (0.50)	0.41 (0.49)	0.48 (0.50)
60-69 years	0.30 (0.46)	0.35 (0.48)	0.36 (0.48)	0.31 (0.46)
70-79 years	0.15 (0.35)	0.16 (0.37)	0.17 (0.38)	0.16 (0.37)
80+ years	0.04 (0.22)	0.03 (0.18)	0.06 (0.24)	0.05 (0.22)
Female	0.54 (0.50)	0.51 (0.50)	0.53 (0.50)	0.54 (0.50)
Schooling				
No Schooling	0.12 (0.32)	0.32 (0.46)	0.49 (0.50)	0.25 (0.43)
Some Primary	0.37 (0.48)	0.19 (0.39)	0.12 (0.32)	0.34 (0.48)
Primary	0.07 (0.20)	0.22 (0.41)	0.13 (0.34)	0.18 (0.38)
Lower Secondary	0.15 (0.35)	0.17 (0.37)	0.09 (0.28)	0.13 (0.33)
Upper Secondar	0.21 (0.40)	0.07 (0.25)	0.12 (0.33)	0.03 (0.18)
Post Secondary	0.09 (0.29)	0.04 (0.20)	0.05 (0.22)	0.07 (0.25)
Years of Schooling	6.48 (4.62)	4.61 (4.12)	4.01 (4.78)	4.49 (3.97)
Mental Health				
Likely Being Depressed (%)	0.33 (0.47)	0.39 (0.48)	0.26 (0.44)	0.35 (0.48)
Mothers' Schooling				
No Schooling	0.55 (0.50)	0.92 (0.28)	0.90 (0.30)	0.57 (0.49)
Some Primary	0.20 (0.40)	0.05 (0.21)	0.04 (0.20)	0.28 (0.46)
Primary or higher	0.25 (0.43)	0.04 (0.19)	0.05 (0.23)	0.13 (0.34)
N	7,595	12,191	49,538	11,248

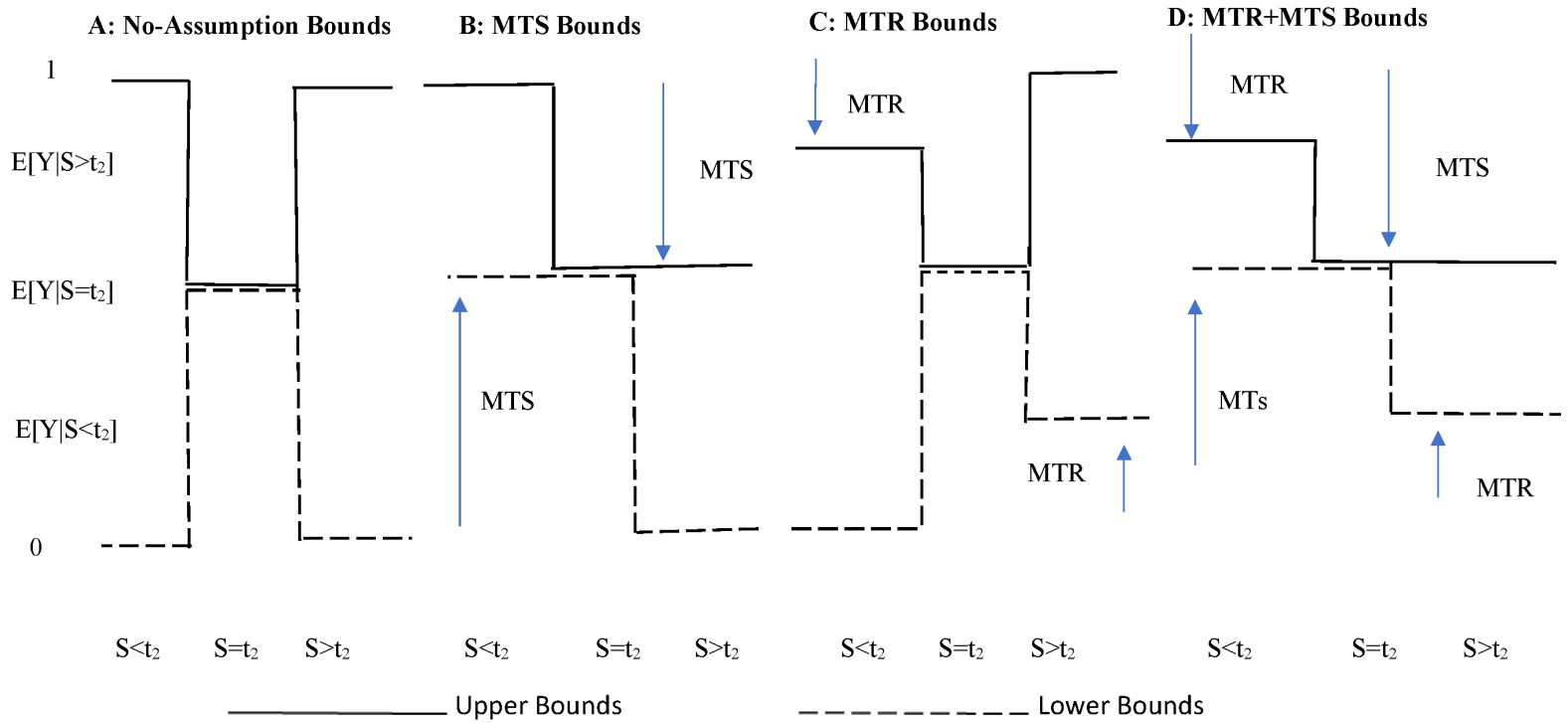
Notes: Weighted summary statistics using country-specific sampling weights. Standard deviations in parentheses. Years of schooling is calculated by assigns 0 years to no schooling, 3 years to some primary, 6 years to primary, 8 years to lower secondary, 12 years to upper secondary, and 14 years to post secondary.

Table 3: Summary Statistics by Gender

	Brazil		China		India		Mexico	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
Demographics								
Age	61.37 (8.94)	61.85 (9.22)	62.29 (8.18)	61.94 (0.43)	63.11 (9.30)	62.47 (9.22)	62.03 (9.42)	61.67 (9.23)
Schooling								
No schooling	0.11 (0.31)	0.13 (0.33)	0.15 (0.35)	0.47 (0.50)	0.33 (0.47)	0.64 (0.48)	0.21 (0.41)	0.28 (0.45)
Some Primary	0.36 (0.48)	0.37 (0.48)	0.20 (0.40)	0.19 (0.39)	0.14 (0.35)	0.10 (0.30)	0.34 (0.47)	0.35 (0.48)
Primary	0.07 (0.26)	0.07 (0.25)	0.28 (0.45)	0.15 (0.36)	0.16 (0.36)	0.11 (0.31)	0.19 (0.39)	0.17 (0.38)
Lower Secondary	0.16 (0.37)	0.13 (0.34)	0.22 (0.42)	0.11 (0.32)	0.12 (0.33)	0.06 (0.24)	0.11 (0.31)	0.14 (0.35)
Upper Secondar	0.22 (0.41)	0.20 (0.40)	0.08 (0.27)	0.05 (0.22)	0.18 (0.38)	0.07 (0.26)	0.04 (0.20)	0.02 (0.15)
Post Secondary	0.09 (0.28)	0.10 (0.30)	0.07 (0.25)	0.03 (0.15)	0.08 (0.27)	0.03 (0.16)	0.10 (0.30)	0.04 (0.20)
Years of Schooling	6.63 (4.56)	6.35 (4.67)	5.98 (3.89)	3.29 (3.90)	5.56 (5.00)	2.64 (4.13)	4.97 (4.27)	4.08 (3.66)
Mental Health								
Likely Being Depressed	0.23 (0.42)	0.42 (0.50)	0.32 (0.46)	0.46 (0.50)	0.24 (0.30)	0.28 (0.45)	0.25 (0.43)	0.43 (0.50)
Mothers' Schooling								
No schooling	0.53 (0.50)	0.57 (0.50)	0.91 (0.28)	0.92 (0.27)	0.90 (0.30)	0.90 (0.30)	0.58 (0.50)	0.57 (0.50)
Some Primary	0.19 (0.39)	0.20 (0.40)	0.05 (0.21)	0.04 (0.20)	0.05 (0.21)	0.04 (0.20)	0.30 (0.46)	0.30 (0.46)
Primary or higher	0.27 (0.45)	0.23 (0.42)	0.04 (0.19)	0.04 (0.19)	0.05 (0.22)	0.06 (0.23)	0.13 (0.33)	0.13 (0.34)
N	3,321	4,274	5,955	6,236	23,269	26,269	5,151	6,097

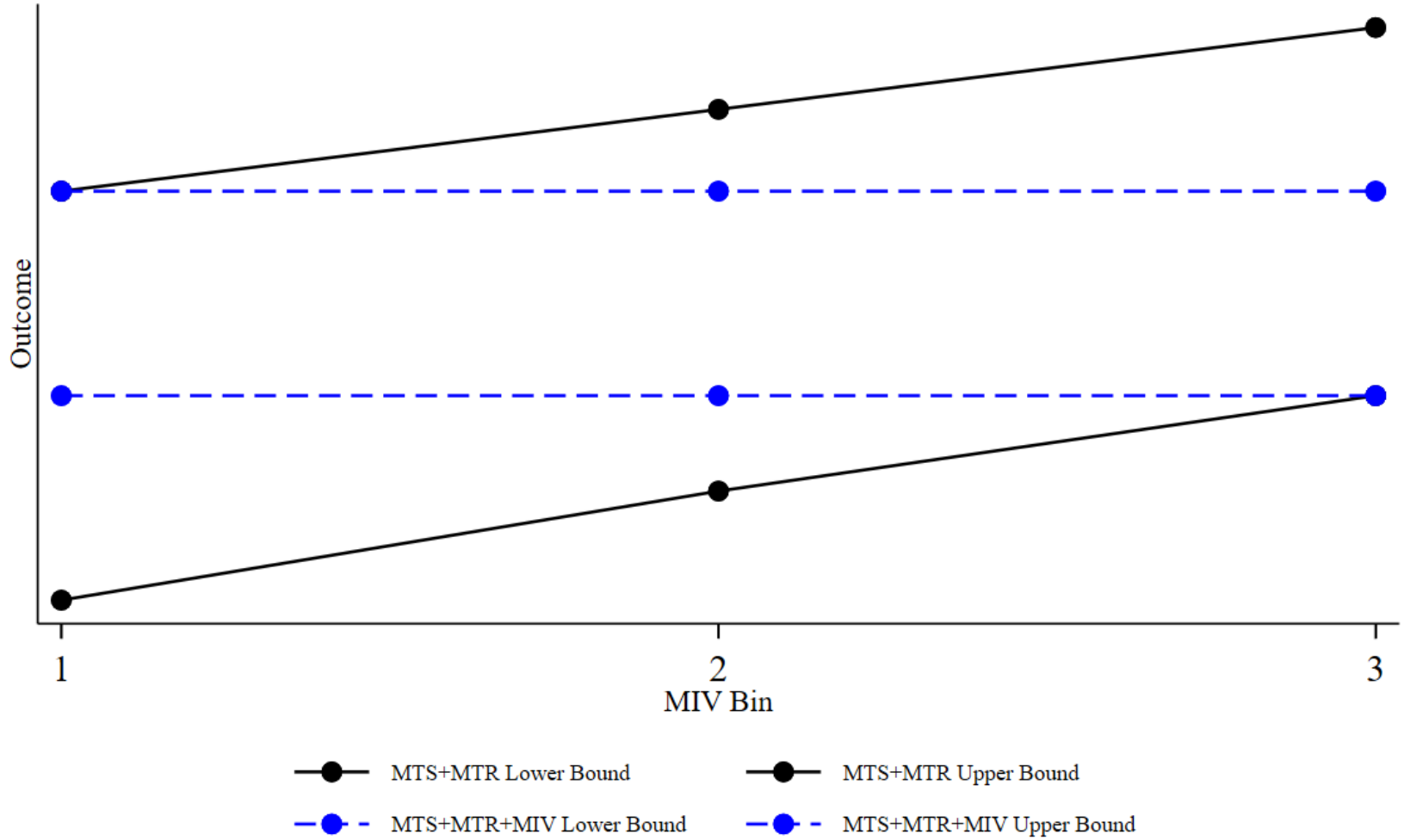
Notes: Weighted summary statistics using country-specific sampling weights. Standard deviations in parentheses. Years of schooling is calculated by assigns 0 years to no schooling, 3 years to some primary, 6 years to primary, 8 years to lower secondary, 12 years to upper secondary, and 14 years to post secondary.

Figure 1: No Assumption, MTS, MTR, and MTS+MTR Bounds on $E[Y(t_2)]$



Each panel illustrates graphically the construction of nonparametric bounds on E[Y(t_2)] under a given assumption. The x-axis represents levels of the realized schooling (S) while the y-axis represents values of the outcome (Y). Panel A illustrates the construction of the no-assumption bounds where the maximum (1) and minimum (0) in the case of a binary outcome are used to replace the missing counterfactuals for those with S<t_2 and S >t_2. In panel B, the MTS assumption tightens the lower and upper bounds relative to the no-assumption bounds by using the observed mean outcomes for those receiving t_2 (E[Y| S=t_2]) to replace the missing counterfactuals for those with S<t_2 and S>t_2. In panel C, the MTR assumption reduces the upper bound for those with S<t_2 by using the observed mean outcome for those with S>t_2 (E[Y|S>t_2]). Correspondingly, the MTR assumption increases the lower bound for those with S>t_2 by using the observed mean outcome for those with S<t_2 (E[Y|S<t_2]). Panel D shows the bounds when imposing the MTS and MTR assumptions together.

Figure 2: MTS+MTR+MIV Bounds



Notes: Construction of MTS+MTR+MIV bounds obtained with a weakly decreasing MIV (Z) divided into 3 bins. For a bin where Z=m, the MTS+MTR+MIV lower bound is obtained by taking the largest MTS+MTR lower bound over all bins where Z≥m. MTS+MTR+MIV upper bound is obtained by taking the smallest MTS+MTR upper bound over all bins where Z≤m. Figure based on De Hann (2011).

Table 4: Probability of Likely Being Depressed by Schooling

Sample	Full	Men	Women
A: Brazil			
No Schooling	0.40 (0.49)	0.29 (0.46)	0.48 (0.50)
Some Primary	0.37 (0.48)	0.26 (0.44)	0.45 (0.50)
Primary	0.38 (0.49)	0.30 (0.46)	0.45 (0.50)
Lower Secondary	0.34 (0.48)	0.25 (0.43)	0.45 (0.50)
Upper Secondar	0.27 (0.45)	0.18 (0.38)	0.37 (0.48)
Post Secondary	0.19 (0.39)	0.11 (0.31)	0.25 (0.43)
B: China			
No Schooling	0.49 (0.50)	0.41 (0.49)	0.52 (0.50)
Some Primary	0.44 (0.50)	0.38 (0.49)	0.49 (0.50)
Primary	0.36 (0.48)	0.33 (0.47)	0.43 (0.49)
Lower Secondary	0.29 (0.45)	0.26 (0.44)	0.34 (0.47)
Upper Secondar	0.24 (0.43)	0.22 (0.42)	0.28 (0.45)
Post Secondary	0.14 (0.35)	0.13 (0.33)	0.20 (0.40)
C: India			
No Schooling	0.30 (0.46)	0.28 (0.45)	0.30 (0.46)
Some Primary	0.25 (0.43)	0.25 (0.44)	0.25 (0.43)
Primary	0.24 (0.43)	0.23 (0.43)	0.23 (0.42)
Lower Secondary	0.23 (0.42)	0.23 (0.42)	0.24 (0.42)
Upper Secondar	0.20 (0.41)	0.19 (0.39)	0.23 (0.42)
Post Secondary	0.16 (0.37)	0.16 (0.37)	0.16 (0.37)
D: Mexico			
No Schooling	0.46 (0.50)	0.35 (0.48)	0.53 (0.50)
Some Primary	0.37 (0.48)	0.27 (0.44)	0.46 (0.50)
Primary	0.31 (0.46)	0.22 (0.41)	0.40 (0.49)
Lower Secondary	0.27 (0.45)	0.22 (0.42)	0.31 (0.46)
Upper Secondar	0.16 (0.36)	0.14 (0.35)	0.18 (0.39)
Post Secondary	0.16 (0.37)	0.12 (0.33)	0.24 (0.43)

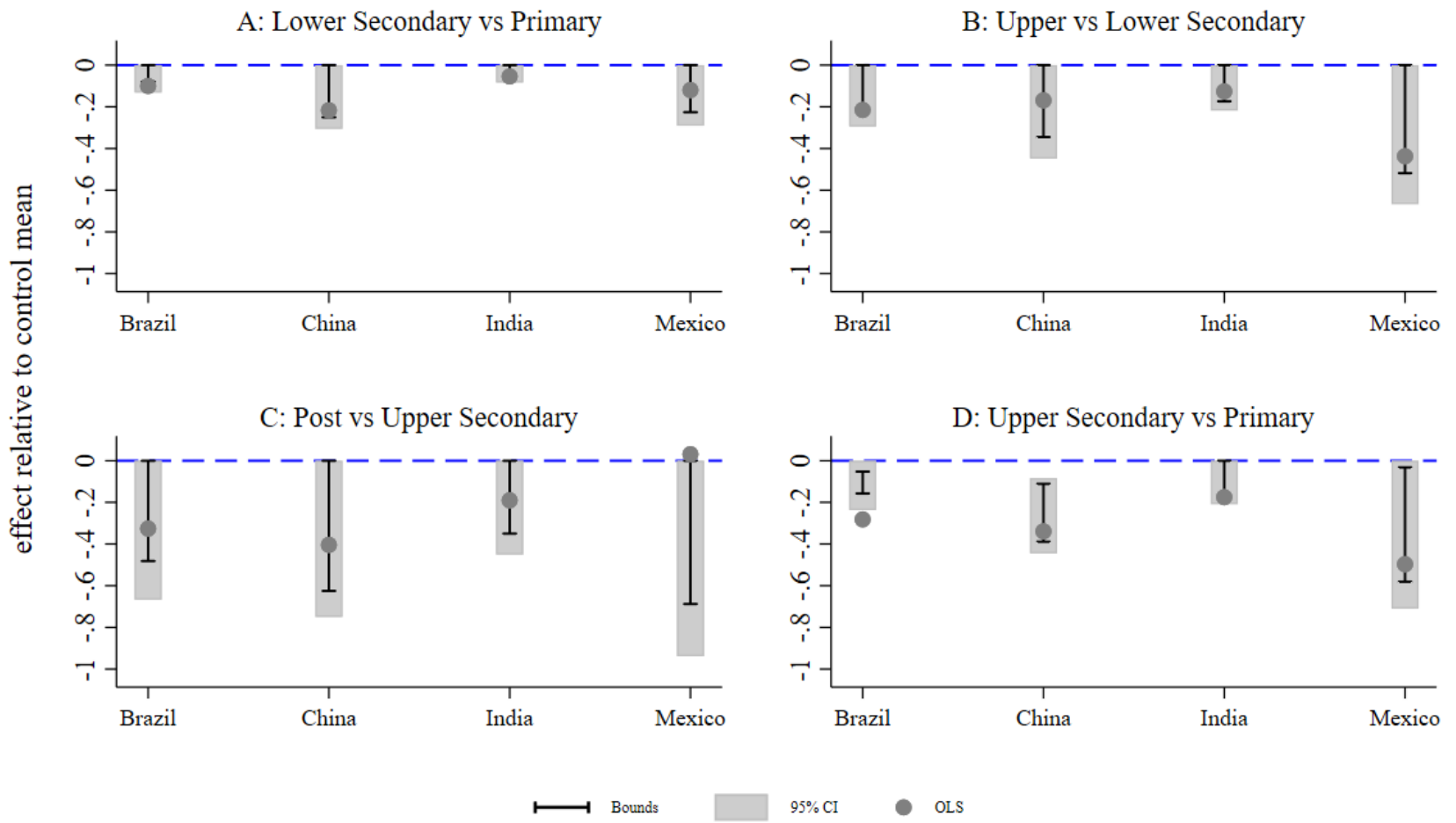
Notes: Weighted summary statistics using country-specific sampling weights. Standard deviations in parentheses.

Table 5: OLS Estimates and Bounds for Effects of Primary Schooling

Country	Control Mean	OLS	NA	MTS	MTR	MTS+MTR	MTS+MTR+MIV
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Some Primary vs No Schooling							
Brazil	0.40	-0.035 (0.028)	[-0.80, 0.72] (-0.81, 0.74)	[-0.23, 0.39] (-0.27, 0.41)	[-0.64, 0.00] (-0.66, 0.00)	[-0.07, 0.00] (-0.12, 0.00)	[-0.09, 0.00] (-0.13, 0.00)
China	0.49	-0.055*** (0.013)	[-0.76, 0.74] (-0.76, 0.74)	[-0.27, 0.46] (-0.29, 0.47)	[-0.61, 0.00] (-0.61, 0.00)	[-0.12, 0.00] (-0.12, 0.00)	[-0.12, 0.00] (-0.14, 0.00)
India	0.30	-0.047*** (0.007)	[-0.62, 0.77] (-0.63, 0.77)	[-0.15, 0.47] (-0.15, 0.48)	[-0.54, 0.00] (-0.54, 0.00)	[-0.06, 0.00] (-0.07, 0.00)	[-0.06, 0.00] (-0.07, 0.00)
Mexico	0.46	-0.085*** (0.012)	[-0.74, 0.67] (-0.74, 0.68)	[-0.24, 0.42] (-0.26, 0.43)	[-0.63, 0.00] (-0.64, 0.00)	[-0.13, 0.00] (-0.15, 0.00)	[-0.13, 0.00] (-0.15, 0.00)
B: Primary vs Some Primary							
Brazil	0.37	0.015 (0.036)	[-0.74, 0.82] (-0.75, 0.84)	[-0.23, 0.50] (-0.26, 0.53)	[-0.55, 0.00] (-0.57, 0.00]	[-0.03, 0.00] (-0.08, 0.00)	[-0.003, 0.00] (-0.03, 0.00)
China	0.44	-0.070*** (0.013)	[-0.81, 0.78] (-0.82, 0.79)	[-0.35, 0.47] (-0.37, 0.48)	[-0.58, 0.00] (-0.59, 0.00)	[-0.12, 0.00] (-0.14, 0.00)	[-0.06, 0.00] (-0.07, 0.00)
India	0.25	-0.007 (0.008)	[-0.88, 0.87] (-0.88, 0.88)	[-0.44, 0.55] (-0.45, 0.56)	[-0.48, 0.00] (-0.49, 0.00)	[-0.04, 0.00] (-0.05, 0.00)	[-0.03, 0.00] (-0.04, 0.00)
Mexico	0.37	-0.062*** (0.013)	[-0.72, 0.75] (-0.73, 0.75)	[-0.28, 0.50] (-0.30, 0.51)	[-0.54, 0.00] (-0.55, 0.00)	[-0.10, 0.00] (-0.12, 0.00)	[-0.07, 0.00] (-0.08, 0.00)
C: Primary vs No Schooling							
Brazil	0.40	-0.019 (0.038)	[-0.90, 0.91] (-0.92, 0.92)	[-0.19, 0.63] (-0.24, 0.60)	[-0.79, 0.00] (-0.79, 0.00)	[-0.07, 0.00] (-0.12, 0.00)	[-0.08, 0.00] (-0.13, 0.00)
China	0.49	-0.125*** (0.012)	[-0.76, 0.71] (-0.77, 0.71)	[-0.23, 0.53] (-0.24, 0.54)	[-0.69, 0.00] (-0.70, 0.00)	[-0.15, 0.00] (-0.17, 0.00)	[-0.16, -0.01] (-0.17, -0.01)
India	0.30	-0.054*** (0.006)	[-0.62, 0.76] (-0.63, 0.76)	[-0.12, 0.56] (-0.13, 0.56)	[-0.57, 0.00] (-0.57, 0.00)	[-0.07, 0.00] (-0.07, 0.00)	[-0.07, -0.02] (-0.08, -0.02)
Mexico	0.46	-0.147*** (0.014)	[-0.81, 0.76] (-0.82, 0.77)	[-0.22, 0.61] (-0.24, 0.62)	[-0.76, 0.00] (-0.77, 0.00)	[-0.17, 0.00] (-0.19, 0.00)	[-0.17, -0.02] (-0.19, -0.01)

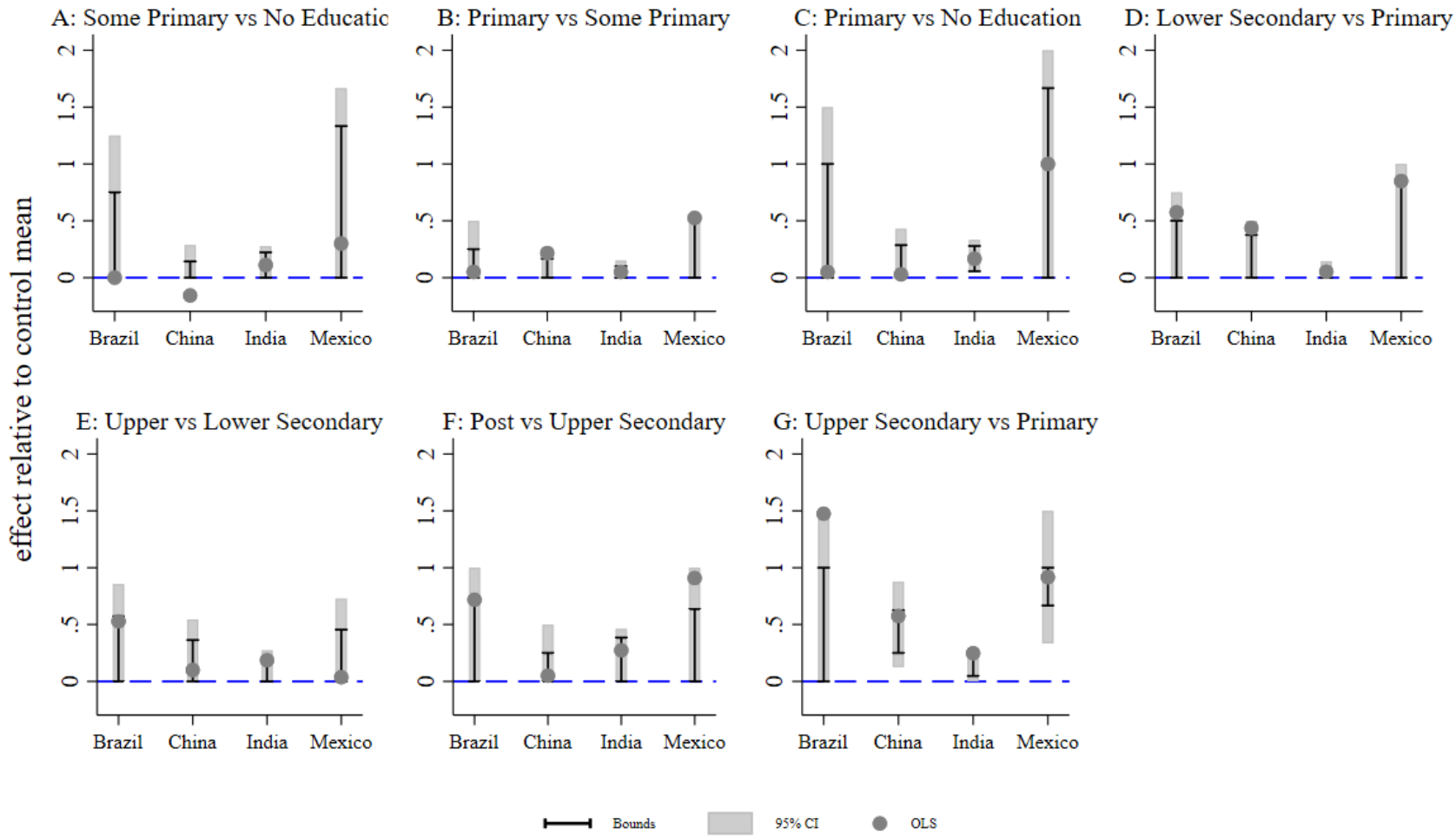
Notes: OLS estimates are from regressions of the depression indicator on dummy variables for the schooling comparisons. Robust standard errors in (.) in column 3.***p<0.01 **p<0.05 *p<0.10. In columns 4-8 estimated bounds are in [.] and corresponding 95% confidence intervals in (.) are from 999 bootstrap replications. Mothers' schooling with bins for no schooling, primary, and primary or higher used as the MIV in column 8. Country-specific sampling weights are applied to OLS regressions and estimated bounds.

Figure 3: MTS+MTR+MIV Bounds for Effects of Secondary Schooling on Probability of Being Likely Depressed



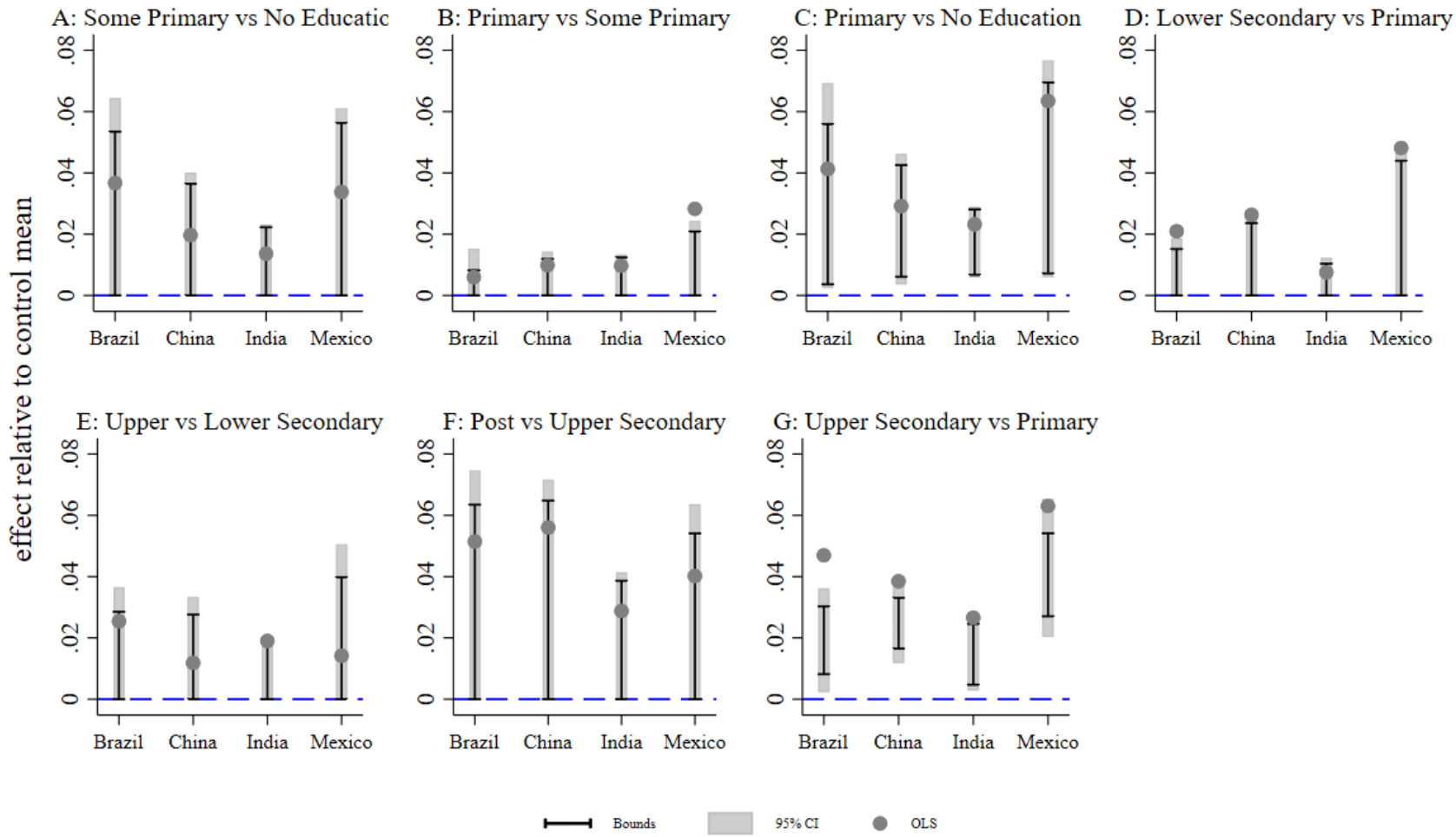
Notes: The y-axis indicates the size of the effects relative to the corresponding "control" mean. The control group in panels A and E are individuals with primary schooling. Individuals with lower seconday and upper secondary represent the control group in panel B and C. The bands indicate the estimated bounds while the large dots represent the corresponding OLS estimate from regressions of the depression indicator on dummy variables for schooling comparisons. The shaded boxes represent the valid 95% confidence intervals on the parameter of interest obtained using the Chernozhukov et al. (2013) method. Mothers' schooling with bins for no schooling, some primary, and primary or higher was used as the MIV.

Figure 4: MTS+MTR+MIV Bounds for Effects of Schooling on Probability of Being in Excellent or Very Good Health



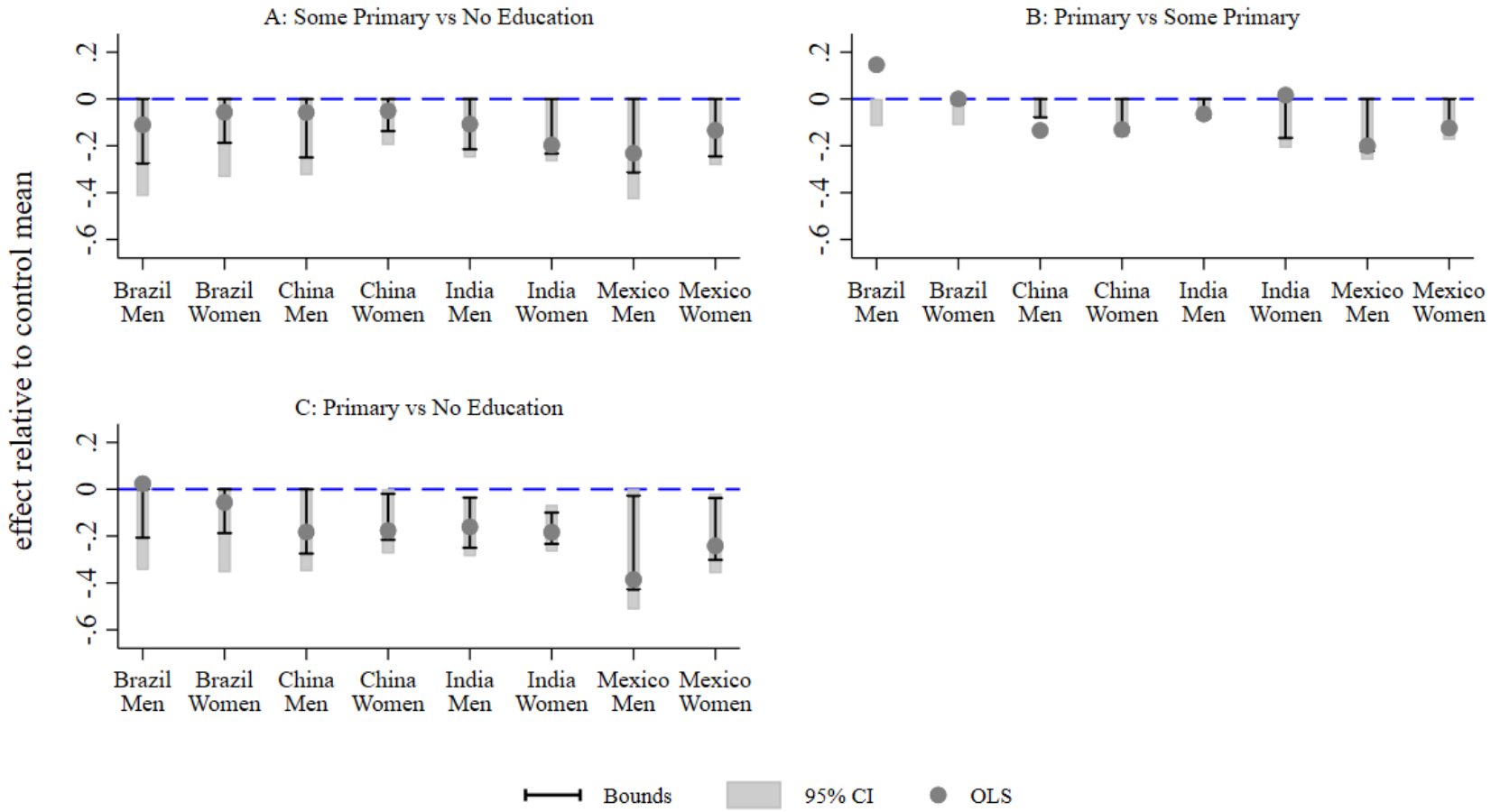
Notes: The y-axis indicates the size of the effects relative to the corresponding "control" mean. The bands indicate the estimated bounds while the large dots represent the corresponding OLS estimate from regressions of the depression indicator on dummy variables for schooling comparisons. The shaded boxes represent the valid 95% confidence intervals on the parameter of interest obtained using the Chernozhukov et al. (2013) method. Mothers' schooling with bins for no schooling, some primary, and primary or higher was used as the MIV.

Figure 5: MTS+MTR+MIV Bounds for Effects of Schooling on Log Household Consumption Per Capita



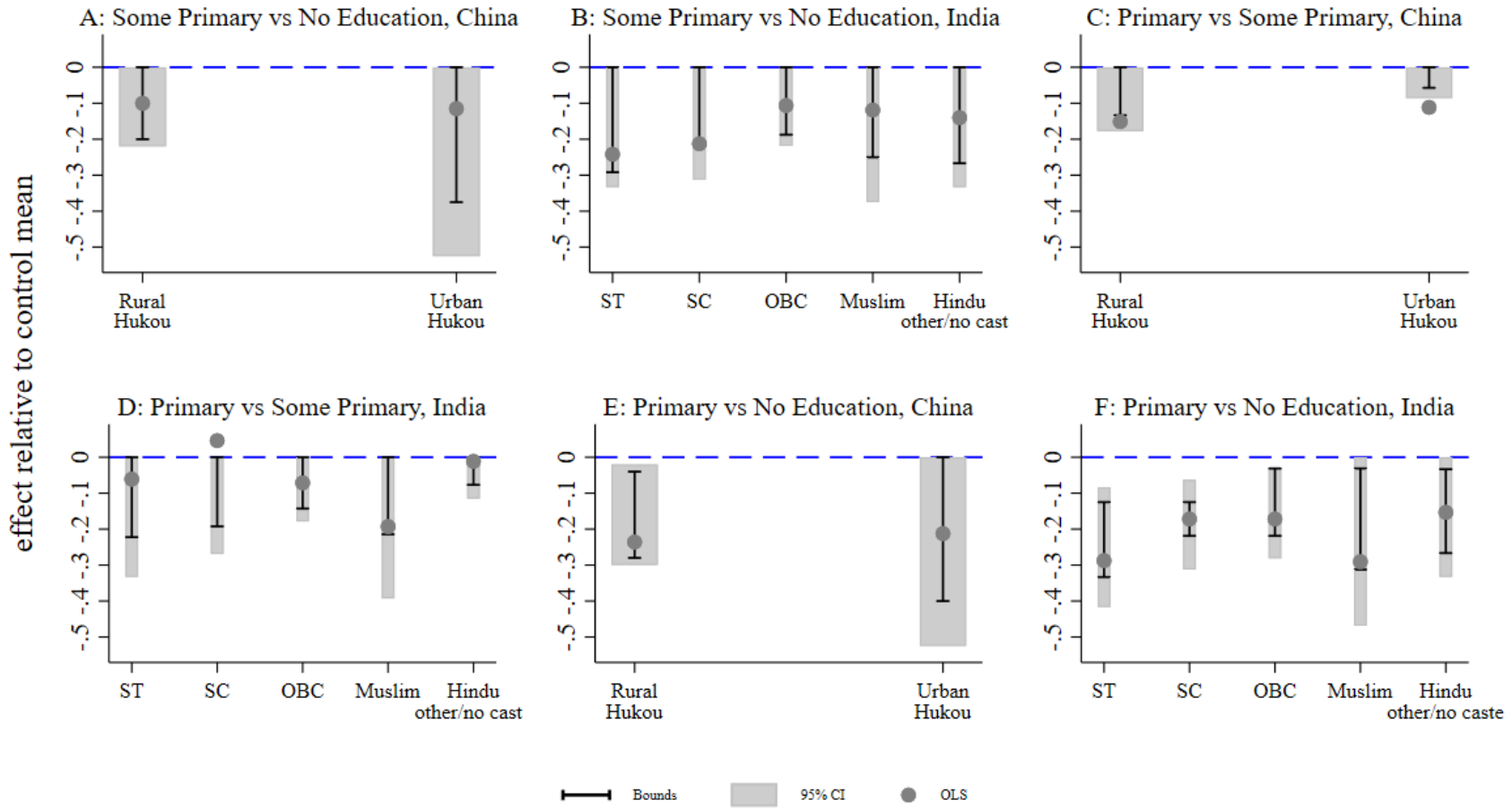
Notes: The y-axis indicates the size of the effects relative to the corresponding "control" mean. The bands indicate the estimated bounds while the large dots represent the corresponding OLS estimate from regressions of the depression indicator on dummy variables for schooling comparisons. The shaded boxes represent the valid 95% confidence intervals on the parameter of interest obtained using the Chernozhukov et al. (2013) method. Mothers' schooling with bins for no education, some primary, and primary or higher was used as the MIV.

Figure 6: MTS+MTR+MIV Bounds for Effects of Primary Schooling on Probability of Likely Being Depressed by Gender



Notes: The y-axis indicates the size of the effects relative to the corresponding "control" mean The bands indicate the estimated bounds while the large dots represent the corresponding OLS estimate from regressions of the depression indicator on dummy variables for schooling comparisons. The shaded boxes represent the valid 95% confidence intervals on the parameter of interest obtained using the Chernozhukov et al. (2013) method. Mothers' schooling with bins for no schooling, some primary, and primary or higher was used as the MIV. In Panel B, estimated bounds for men in Mexico are [0.01, 0.00]. This is not shown as the lower bounds is greater than the upper bounds.

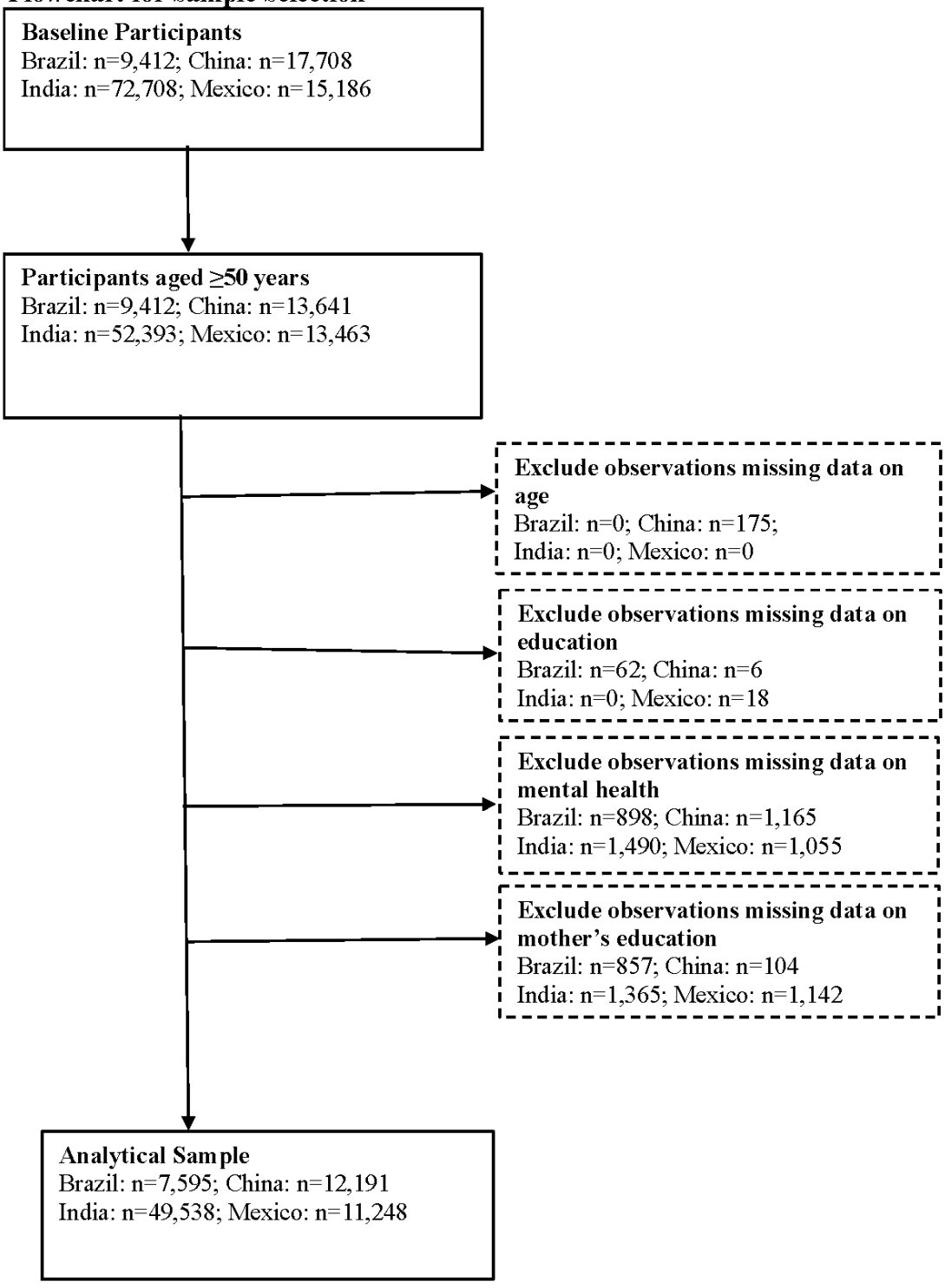
Figure 7: MTS+MTR+MIV Bounds for Effects of Primary Schooling on Probability of Likely Being Depressed By Social Identity



Notes: The y-axis indicates the size of the effects relative to the corresponding "control" mean. The bands indicate the estimated bounds while the large dots represent the corresponding OLS estimate from regressions of the depression indicator on dummy variables for schooling comparisons. The shaded boxes represent the valid 95% confidence intervals on the parameter of interest obtained using the Chernozhukov et al. (2013) method. Mothers' schooling with bins for no schooling, some primary, and primary or higher was used as the MIV. SC: Scheduled Castes; ST: Scheduled Tribes; OBC: Other Backward Classes.

APPENDIX A: ADDITIONAL TABLES AND FIGURES

Figure A1: Flowchart for Sample Selection



Appendix Table A1: Proportion of Individuals with Mothers who had no schooling, by own schooling

	Brazil	**China**	**India**	**Mexico**
No Schooling	0.92 (0.26)	0.97 (0.16)	0.99 (0.10)	0.87 (0.34)
Some Primary	0.70 (0.46)	0.94 (0.24)	0.92 (0.26)	0.64 (0.48)
Primary	0.56 (0.50)	0.92 (0.27)	0.89 (0.31)	0.47 (0.50)
Lower Secondary	0.47 (0.50)	0.86 (0.35)	0.83 (0.38)	0.26 (0.44)
Upper Secondary	0.30 (0.46)	0.79 (0.41)	0.74 (0.44)	0.20 (0.40)
Post Secondary	0.18 (0.39)	0.78 (0.41)	0.56 (0.50)	0.15 (0.36)

Notes: Weighted summary statistics. Standard deviations in parentheses.

Appendix Table A2: OLS Estimates and Bounds for Effects of Secondary Schooling

	Control Mean	OLS	MTS+MTR+MIV
	(1)	(2)	(3)
A: Lower Secondary vs Primary			
Brazil	0.38	-0.034 (0.036)	[-0.03, 0.00] (-0.05, 0.00)
China	0.36	-0.078*** (0.014)	[-0.09, 0.00] (0.11, 0.00)
India	0.24	-0.013 (0.009)	[-0.01, 0.00] (-0.02, 0.00)
Mexico	0.31	-0.037** (0.016)	[-0.07, 0.00] (-0.10, 0.00)
B: Upper vs Lower Secondary			
Brazil	0.34	-0.073*** (0.023)	[-0.07, 0.00] (-0.10, 0.00)
China	0.29	-0.049*** (0.018)	[-0.10, 0.00] (-0.13, 0.00)
India	0.23	-0.029*** (0.008)	[-0.04, 0.00] (-0.05, 0.00)
Mexico	0.27	-0.118*** (0.022)	[-0.14, 0.00] (-0.18, 0.00)
C: Post vs Upper Secondary			
Brazil	0.27	-0.088*** (0.022)	[-0.13, 0.00] (-0.18, 0.00)
China	0.24	-0.097*** (0.021)	[-0.15, 0.00] (-0.18, 0.00)
India	0.20	-0.038*** (0.009)	[-0.07, 0.00] (-0.09, 0.00)
Mexico	0.16	0.006 (0.024)	[-0.11, 0.00] (-0.15, 0.00)
D: Upper Secondary vs Primary			
Brazil	0.38	-0.107*** (0.033)	[-0.06, -0.02] (-0.09, 0.00)
China	0.36	-0.122*** (0.018)	[-0.14, -0.04] (-0.16, -0.03)
India	0.24	-0.042*** (0.008)	[-0.04, 0.00] (-0.05, 0.00)
Mexico	0.31	-0.154*** (0.021)	[-0.18, -0.01] (-0.22, 0.00)

Notes: OLS estimates are from regressions of the depression indicator on dummy variables for the schooling comparisons. Robust standard errors in (.) in column 3.***p<0.01 **p<0.05 *p<0.10. In columns 4 estimated bounds are in [.] and corresponding 95% confidence intervals in (.) are from 999 bootstrap replications. Mothers' schooling with bins for no schooling, primary, and primary or higher used as the MIV. Country-specific sampling weights are applied to OLS regressions and estimated bounds.

Appendix Table A3: OLS Estimates and Bounds for Effects of Schooling on Probability of Being in Excellent/Very Good Health

	Control Mean	OLS	MTS+MTR+MIV
	(1)	(2)	(3)
A: Some Primary vs No Schooling			
Brazil	0.04	0.000 (0.010)	[0.00, 0.03] (0.00, 0.05)
China	0.07	-0.011 (0.008)	[0.00, 0.01] (0.00, 0.02)
India	0.18	0.020*** (0.006)	[0.00, 0.04] (0.00, 0.05)
Mexico	0.03	0.009** (0.004)	[0.00, 0.04] (0.00, 0.05)
B: Primary vs Some Primary			
Brazil	0.04	0.002 (0.011)	[0.00, 0.01] (0.00, 0.02)
China	0.06	0.013 (0.008)	[0.00, 0.01] (0.00, 0.01)
India	0.20	0.010 (0.007)	[0.00, 0.02] (0.00, 0.03)
Mexico	0.04	0.021*** (0.006)	[0.00, 0.02] (0.00, 0.02)
C: Primary vs No Schooling			
Brazil	0.04	0.002 (0.010)	[0.00, 0.04] (0.00, 0.06)
China	0.07	0.002 (0.008)	[0.00, 0.02] (0.00, 0.03)
India	0.18	0.030*** (0.006)	[0.01, 0.05] (0.01, 0.06)
Mexico	0.03	0.030*** (0.006)	[0.00, 0.05] (0.00, 0.06)
D: Lower Secondary vs Primary			
Brazil	0.04	0.023* (0.013)	[0.00, 0.02] (0.00, 0.03)
China	0.08	0.035*** (0.010)	[0.00, 0.03] (0.00, 0.04)
India	0.21	0.011 (0.008)	[0.00, 0.01] (0.00, 0.03)
Mexico	0.06	0.051*** (0.010)	[0.00, 0.05] (0.00, 0.06)
E: Upper vs Lower Secondary			
Brazil	0.07	0.037** (0.014)	[0.00, 0.04] (0.00, 0.06)
China	0.11	0.011 (0.016)	[0.00, 0.04] (0.00, 0.06)
India	0.22	0.041*** (0.009)	[0.00, 0.04] (0.00, 0.06)
Mexico	0.11	0.004 (0.018)	[0.00, 0.05] (0.00, 0.08)
F: Post vs Upper Secondary			

Brazil	0.11	0.079*** (0.024)	[0.00, 0.08] (0.00, 0.11)
China	0.12	0.006 (0.021)	[0.00,0.03] (0.00, 0.06)
India	0.26	0.071*** (0.011)	[0.00, 0.10] (0.00, 0.12)
Mexico	0.11	0.100*** (0.021)	[0.00, 0.07] (0.00, 0.11)
G: Upper Secondary vs Primary			
Brazil	0.04	0.059*** (0.014)	[0.00, 0.04] (0.00, 0.06)
China	0.08	0.046*** (0.015)	[0.02, 0.05] (0.01, 0.07)
India	0.21	0.052*** (0.008)	[0.01, 0.06] (0.00, 0.06)
Mexico	0.06	0.055*** (0.017)	[0.04, 0.06] (0.02, 0.09)

Notes: OLS estimates are from regressions of the self-reported health indicator on dummy variables for the schooling comparisons. Robust standard errors in (.) in column 3.***p<0.01 **p<0.05 *p<0.10. In columns 4 estimated bounds are in [.] and corresponding 95% confidence intervals in (.) are from 999 bootstrap replications. Mothers' schooling with bins for no schooling, primary, and primary or higher used as the MIV. Country-specific sampling weights are applied to OLS regressions and estimated bounds.

Appendix Table A4: OLS Estimates and Bounds for Effects of Schooling on Log Household Consumption Per Capita

	Control Mean	OLS	MTS+MTR+MIV
	(1)	(2)	(3)
A: Some Primary vs No Schooling			
Brazil	8.23	0.302*** (0.045)	[0.00, 0.44] (0.00, 0.53)
China	8.23	0.162*** (0.024)	[0.00, 0.30] (0.00, 0.33)
India	10.34	0.141*** (0.011)	[0.00, 0.23] (0.00, 0.24)
Mexico	8.35	0.282*** (0.029)	[0.00, 0.47] (0.00, 0.51)
B: Primary vs Some Primary			
Brazil	8.53	0.051 (0.066)	[0.00, 0.07] (0.00, 0.13)
China	8.39	0.083*** (0.025)	[0.00, 0.10] (0.00, 0.12)
India	10.48	0.102*** (0.012)	[0.00, 0.13] (0.00, 0.14)
Mexico	8.63	0.244*** (0.026)	[0.00, 0.18] (0.00, 0.21)
C: Primary vs No Schooling			
Brazil	8.23	0.353*** (0.061)	[0.03, 0.46] (0.02, 0.57)
China	8.23	0.245*** (0.023)	[0.05, 0.35] (0.03, 0.38)
India	10.34	0.243*** (0.010)	[0.07, 0.29] (0.06, 0.30)
Mexico	8.35	0.526*** (0.033)	[0.06, 0.58] (0.05, 0.64)
D: Lower Secondary vs Primary			
Brazil	8.58	0.180*** (0.054)	[0.00, 0.13] (0.00, 0.16)
China	8.47	0.223*** (0.027)	[0.00, 0.20] (0.00, 0.23)
India	10.59	0.080*** (0.014)	[0.00, 0.11] (0.00, 0.13)
Mexico	8.87	0.427*** (0.031)	[0.00, 0.39] (0.00, 0.44)
E: Upper vs Lower Secondary			
Brazil	8.76	0.223*** (0.038)	[0.00, 0.25] (0.00, 0.32)
China	8.69	0.103** (0.042)	[0.00, 0.24] (0.00, 0.29)
India	10.67	0.203*** (0.015)	[0.00, 0.21] (0.00, 0.22)
Mexico	9.30	0.132** (0.055)	[0.00, 0.37] (0.00, 0.47)
F: Post vs Upper Secondary			

Brazil	8.98	0.462*** (0.060)	[0.00, 0.57] (0.00, 0.67)
China	8.80	0.493*** (0.056)	[0.00, 0.57] (0.00, 0.63)
India	10.87	0.313*** (0.018)	[0.00, 0.42] (0.00, 0.45)
Mexico	9.43	0.379*** (0.057)	[0.00, 0.51] (0.00, 0.60)
G: Upper Secondary vs Primary			
Brazil	8.58	0.403*** (0.057)	[0.07, 0.26] (0.02, 0.31)
China	8.47	0.326*** (0.041)	[0.14, 0.28] (0.10, 0.33)
India	10.59	0.282*** (0.013)	[0.05, 0.26] (0.03, 0.28)
Mexico	8.87	0.559*** (0.052)	[0.24, 0.48] (0.18, 0.58)

Notes: OLS estimates are from regressions of log household consumption per capita on dummy variables for the schooling comparisons. Robust standard errors in (.) in column 3.***p<0.01 **p<0.05 *p<0.10. In columns 4 estimated bounds are in [.] and corresponding 95% confidence intervals in (.) are from 999 bootstrap replications. Mothers' schooling with bins for no schooling, primary, and primary or higher used as the MIV. Country-specific sampling weights are applied to OLS regressions and estimated bounds.

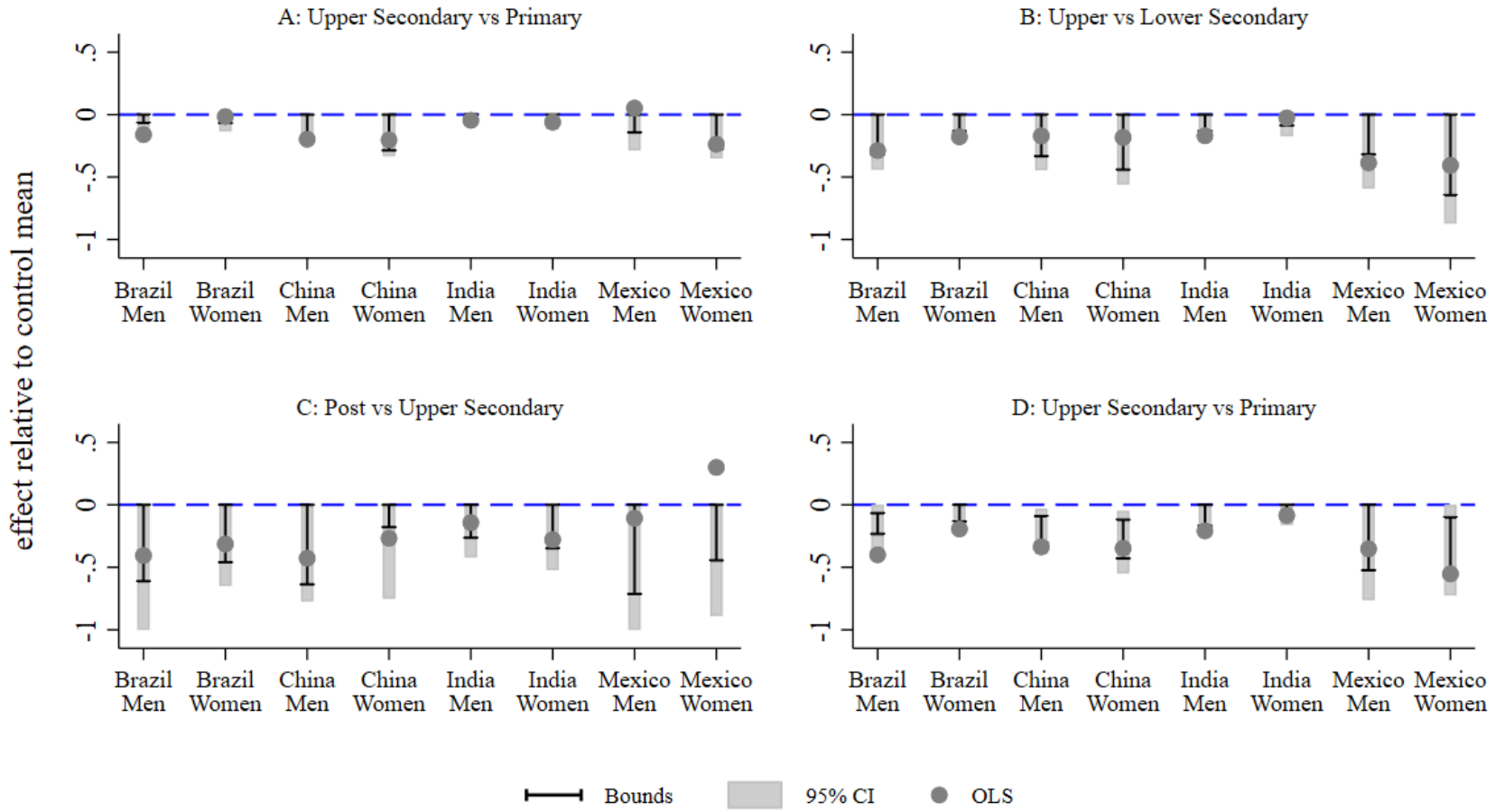
Appendix Table A5: OLS Estimates and Bounds for Effects of Primary Schooling On Probability of Likely Being Depressed By Gender

		Control Mean	OLS	MTS+MTR+MIV
		(1)	(2)	(3)
A: Some Primary vs No Schooling				
Brazil	Men	0.29	-0.032 (0.030)	[-0.08, 0.00] (-0.12, 0.00)
Brazil	Women	0.48	-0.027 (0.033)	[-0.09, 0.00] (-0.16, 0.00)
China	Men	0.40	-0.023 (0.022)	[-0.10, 0.00] (-0.13, 0.00)
China	Women	0.51	-0.026 (0.017)	[-0.07, 0.00] (-0.10, 0.00)
India	Men	0.28	-0.030*** (0.010)	[-0.06, 0.00] (-0.07, 0.00)
India	Women	0.30	-0.059*** (0.010)	[-0.07, 0.00] (-0.08, 0.00)
Mexico	Men	0.35	-0.081*** (0.018)	[-0.11, 0.00] (-0.15, 0.00)
Mexico	Women	0.53	-0.071*** (0.016)	[-0.13, 0.00] (-0.15, 0.00)
B: Primary vs Some Primary				
Brazil	Men	0.26	0.038 (0.040)	[0.01, 0.00] (-0.03, 0.00)
Brazil	Women	0.45	-0.000 (0.042)	[-0.01, 0.00] (-0.05, 0.00)
China	Men	0.38	-0.051*** (0.018)	[-0.03, 0.00] (-0.03, 0.00)
China	Women	0.49	-0.064*** (0.021)	[-0.06, 0.00] (-0.08, 0.00)
India	Men	0.25	-0.016 (0.011)	[-0.02, 0.00] (-0.02, 0.00)
India	Women	0.24	0.004 (0.012)	[-0.04, 0.00] (-0.05, 0.00)
Mexico	Men	0.27	-0.054*** (0.017)	[-0.06, 0.00] (-0.07, 0.00)
Mexico	Women	0.46	-0.057*** (0.018)	[-0.06, 0.00] (-0.08, 0.00)
C: Primary vs No Schooling				
Brazil	Men	0.29	0.007 (0.046)	[-0.06, 0.00] (-0.10, 0.00)
Brazil	Women	0.45	-0.027 (0.049)	[-0.09, 0.00] (-0.17, 0.00)
China	Men	0.40	-0.073*** (0.020)	[-0.11, -0.01] (-0.14, 0.00)
China	Women	0.51	-0.090*** (0.018)	[-0.11, -0.01] (-0.14, 0.00)
India	Men	0.28	-0.045*** (0.009)	[-0.07, -0.01] (-0.08, -0.01)
India	Women	0.30	-0.055***	[-0.07, -0.03]

			(0.009)	(-0.08, -0.02)
Mexico	Men	0.35	-0.135*** (0.020)	[-0.15, -0.01] (-0.18, 0.00)
Mexico	Women	0.53	-0.128*** (0.020)	[-0.16, -0.02] (-0.19, -0.01)

Notes: OLS estimates are from regressions of the depression indicator on dummy variables for the schooling comparisons. Robust standard errors in (.) in column 3.***p<0.01 **p<0.05 *p<0.10. In columns 4 estimated bounds are in [.] and corresponding 95% confidence intervals in (.) are from 999 bootstrap replications. Mothers' schooling with bins for no schooling, primary, and primary or higher used as the MIV. Country-specific sampling weights are applied to OLS regressions and estimated bounds.

Figure A2: MTS+MTR+MIV Bounds for Effects Secondary Schooling on the Probability of Likely Being Depressed By Gender



Notes: The y-axis indicates the size of the effects relative to the corresponding "control" mean. The bands indicate the estimated bounds while the large dots represent the corresponding OLS estimate from regressions of the depression indicator on dummy variables for schooling comparisons. The shaded boxes represent the valid 95% confidence intervals on the parameter of interest obtained using the Chernozhukov et al. (2013) method. Mothers' schooling with bins for no schooling, some primary, and primary or higher was used as the MIV.

Appendix Table A6: OLS Estimates and Bounds for Effects of Secondary Schooling On Probability of Likely Being Depressed By Gender

		Control Mean	OLS	MTS+MTR+MIV
		(1)	(2)	(3)
A: Lower Secondary vs Primary				
Brazil	Men	0.30	-0.048 (0.046)	[-0.02, 0.00] (-0.05, 0.00)
Brazil	Women	0.45	-0.007 (0.043)	[-0.03, 0.00] (-0.06, 0.00)
China	Men	0.33	-0.065*** (0.017)	[-0.06, 0.00] (-0.08, 0.00)
China	Women	0.42	-0.085*** (0.024)	[-0.12, 0.00] (-0.14, 0.00)
India	Men	0.24	-0.011 (0.011)	[-0.01, 0.00] (-0.02, 0.00)
India	Women	0.25	-0.015 (0.014)	[-0.01, 0.00] (-0.03, 0.00)
Mexico	Men	0.21	0.011 (0.023)	[-0.03, 0.00] (-0.06, 0.00)
Mexico	Women	0.40	-0.095*** (0.021)	[-0.11, 0.00] (-0.14, 0.00)
B: Upper vs Lower Secondary				
Brazil	Men	0.25	-0.072*** (0.022)	[-0.08, 0.00] (-0.11, 0.00)
Brazil	Women	0.45	-0.080** (0.037)	[-0.06, 0.00] (-0.10, 0.00)
China	Men	0.27	-0.046** (0.022)	[-0.09, 0.00] (-0.12, 0.00)
China	Women	0.34	-0.062* (0.031)	[-0.15, 0.00] (-0.19, 0.00)
India	Men	0.23	-0.039*** (.010)	[-0.03, 0.00] (-0.04, 0.00)
India	Women	0.23	-0.006 (0.015)	[-0.02, 0.00] (-0.04, 0.00)
Mexico	Men	0.22	-0.085*** (0.031)	[-0.07, 0.00] (-0.13, 0.00)
Mexico	Women	0.31	-0.126*** (0.034)	[-0.20, 0.00] (-0.27, 0.00)
C: Post vs Upper Secondary				
Brazil	Men	0.18	-0.073** (0.028)	[-0.11, 0.00] (-0.18, 0.00)
Brazil	Women	0.37	-0.116*** (0.029)	[-0.17, 0.00] (-0.24, 0.00)
China	Men	0.22	-0.094 (0.025)	[-0.14, 0.00] (-0.17, 0.00)
China	Women	0.28	-0.075* (0.042)	[-0.05, 0.00] (-0.21, 0.00)
India	Men	0.19	-0.027** (0.011)	[-0.05, 0.00] (-0.08, 0.00)
India	Women	0.23	-0.064***	[-0.08, 0.00]

			(0.017)	(-0.12, 0.00)
Mexico	Men	0.14	-0.015 (0.028)	[-0.10, 0.00] (-0.14, 0.00)
Mexico	Women	0.18	0.054 (0.040)	[-0.08, 0.00] (-0.16, 0.00)
D: Upper Secondary vs Primary				
Brazil	Men	0.30	-0.120*** (0.041)	[-0.07, -0.02] (-0.11, 0.00)
Brazil	Women	0.45	-0.087** (0.037)	[-0.06, 0.00] (-0.10, 0.00)
China	Men	0.33	-0.111*** (0.022)	[-0.10, -0.03] (-0.13, -0.01)
China	Women	0.42	-0.146*** (0.030)	[-0.18, -0.05] (-0.23, -0.22)
India	Men	0.24	-0.050*** (0.010)	[-0.04, 0.00] (-0.05, 0.00)
India	Women	0.25	-0.021 (0.013)	[-0.02, 0.00] (-0.04, 0.00)
Mexico	Men	0.21	-0.074*** (0.027)	[-0.11, 0.00] (-0.16, 0.00)
Mexico	Women	0.40	-0.221*** (0.034)	[-0.23, -0.04] (-0.29, 0.00)

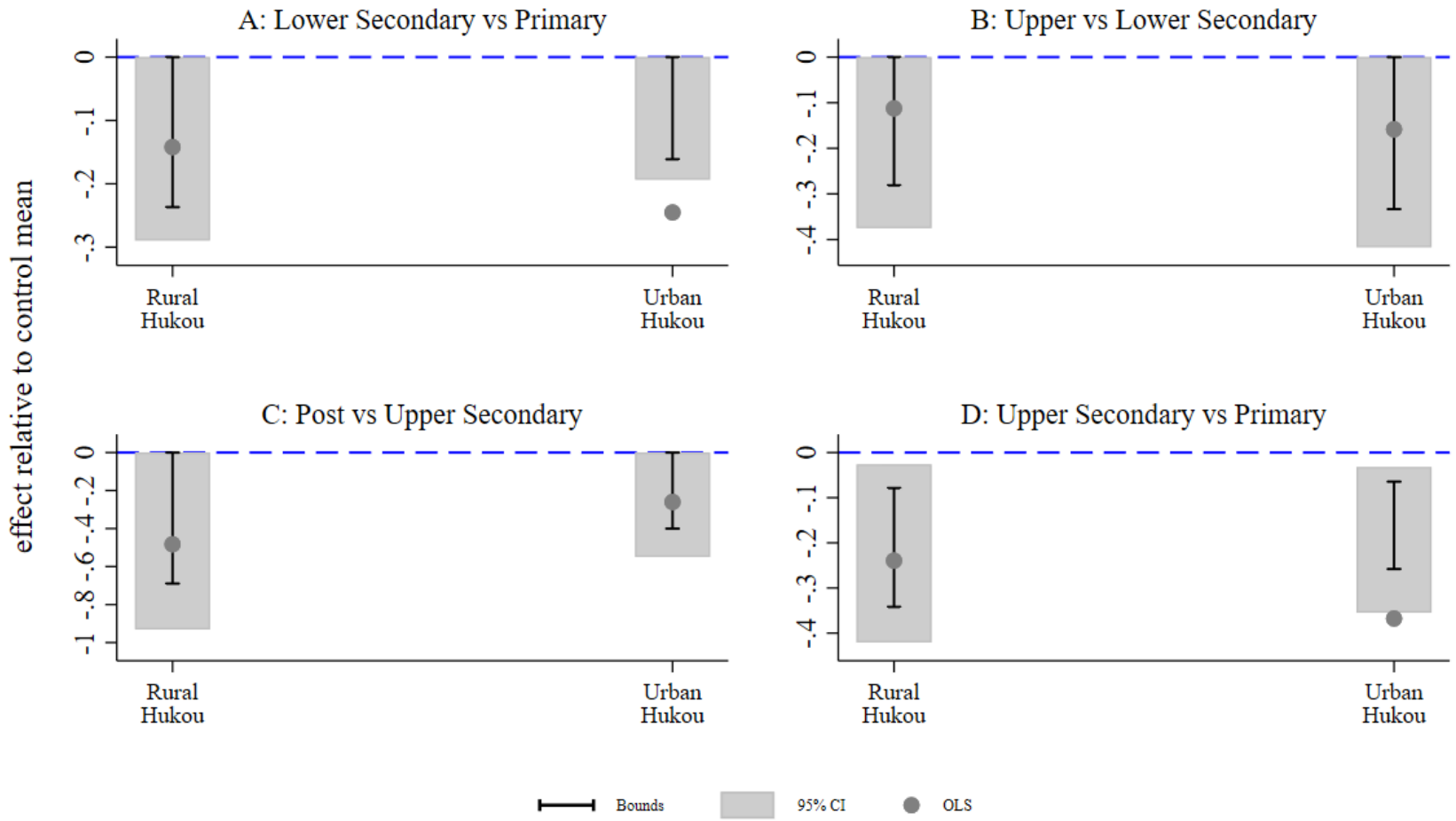
Notes: OLS estimates are from regressions of the depression indicator on dummy variables for the schooling comparisons. Robust standard errors in (.) in column 3.***p<0.01 **p<0.05 *p<0.10. In columns 4 estimated bounds are in [.] and corresponding 95% confidence intervals in (.) are from 999 bootstrap replications. Mothers' schooling with bins for no schooling, primary, and primary or higher used as the MIV. Country-specific sampling weights are applied to OLS regressions and estimated bounds.

Appendix Table A7: OLS Estimates and Bounds for Effects of Primary Schooling On Probability of Likely Being Depressed By Social Identity

		Control Mean	OLS	MTS+MTR+MIV
		(1)	(2)	(3)
A: Some Primary vs No Schooling				
China	Rural Hukou	0.50	-0.050*** (0.014)	[-0.10, 0.00] (-0.11, 0.00)
China	Urban Hukou	0.40	-0.046 (0.039)	[-0.15, 0.00] (-0.21, 0.00)
India	Scheduled Tribe	0.24	-0.058*** (0.013)	[-0.07, 0.00] (-0.08, 0.00)
India	Scheduled Caste	0.32	-0.068*** (0.017)	[-0.07, 0.00] (-0.10, 0.00)
India	OBC	0.32	-0.034*** (0.012)	[-0.06, 0.00] (-0.07, 0.00)
India	Muslim	0.32	-0.038 (0.034)	[-0.08, 0.00] (-0.12, 0.00)
India	Hindu, other/no caste	0.30	-0.042*** (0.016)	[-0.08, 0.00] (-0.10, 0.00)
B: Primary vs Some Primary				
China	Rural Hukou	0.45	-0.068*** (0.015)	[-0.06, 0.00] (-0.08, 0.00)
China	Urban Hukou	0.35	-0.039 (0.034)	[-0.02, 0.00] (-0.03, 0.00)
India	Scheduled Tribe	0.18	-0.011 (0.017)	[-0.04, 0.00] (-0.06, 0.00)
India	Scheduled Caste	0.26	0.012 (0.022)	[-0.05, 0.00] (-0.07, 0.00)
India	OBC	0.28	-0.020 (0.014)	[-0.04, 0.00] (-0.05, 0.00)
India	Muslim	0.28	-0.054 (0.040)	[-0.06, 0.00] (-0.11, 0.00)
India	Hindu, other/no caste	0.26	-0.003 (0.018)	[-0.02, 0.00] (-0.03, 0.00)
C: Primary vs No Schooling				
China	Rural Hukou	0.50	-0.118*** (0.014)	[-0.14, -0.02] (-0.15, -0.01)
China	Urban Hukou	0.40	-0.085** (0.034)	[-0.16, 0.00] (-0.21, 0.00)
India	Scheduled Tribe	0.24	-0.069*** (0.014)	[-0.08, -0.03] (-0.10, -0.02)
India	Scheduled Caste	0.32	-0.055*** (0.018)	[-0.07, -0.04] (-0.10, -0.02)
India	OBC	0.32	-0.055*** (0.011)	[-0.07, -0.01] (-0.09, -0.01)
India	Muslim	0.32	-0.093*** (0.030)	[-0.10, -0.01] (-0.15, 0.00)
India	Hindu, other/no caste	0.30	-0.046*** (0.015)	[-0.08, -0.01] (-0.10, 0.00)

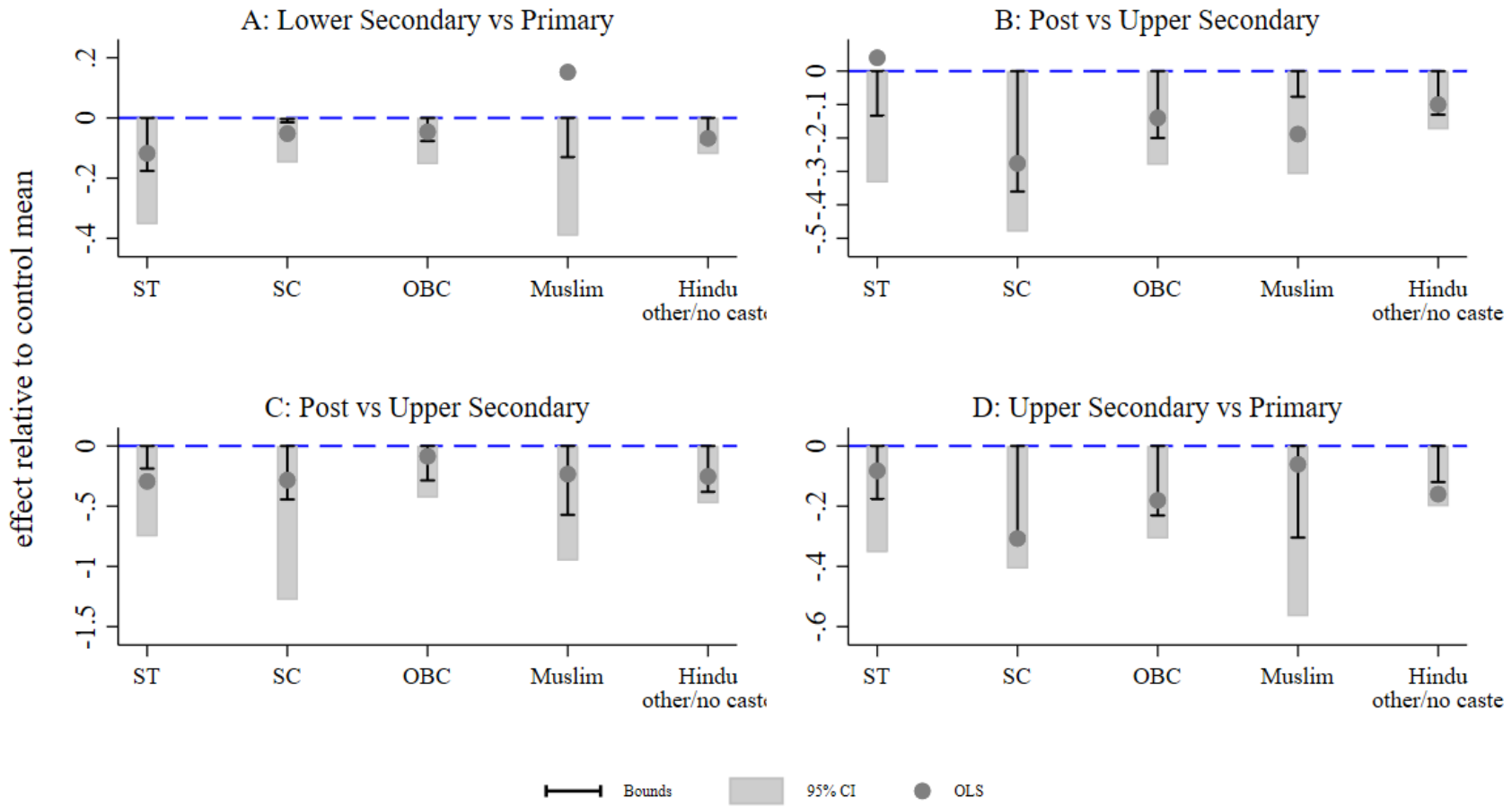
Notes: OLS estimates are from regressions of the depression indicator on dummy variables for the schooling comparisons. Robust standard errors in (.) in column 3.***p<0.01 **p<0.05 *p<0.10. In columns 4 estimated bounds are in [.] and corresponding 95% confidence intervals in (.) are from 999 bootstrap replications. Mothers' schooling with bins for no schooling, primary, and primary or higher used as the MIV. Country-specific sampling weights are applied to OLS regressions and estimated bounds.

Figure A3: MTS+MTR+MIV Bounds for Effects of Secondary Schooling on Probability of Likely Being Depressed By Social Identity in China



Notes: The y-axis indicates the size of the effects relative to the corresponding "control" mean. The bands indicate the estimated bounds while the large dots represent the corresponding OLS estimate from regressions of the depression indicator on dummy variables for schooling comparisons. The shaded boxes represent the valid 95% confidence intervals on the parameter of interest obtained using the Chernozhukov et al. (2013) method. Mothers' schooling with bins for no schooling, some primary, and primary or higher was used as the MIV.

Figure A4: MTS+MTR+MIV Bounds for Effects of Secondary Schooling on Probability of Likely Being Depressed By Social Identity in India



Notes: The y-axis indicates the size of the effects relative to the corresponding "control" mean. The bands indicate the estimated bounds while the large dots represent the corresponding OLS estimate from regressions of the depression indicator on dummy variables for schooling comparisons. The shaded boxes represent the valid 95% confidence intervals on the parameter of interest obtained using the Chernozhukov et al. (2013) method. Mothers' schooling with bins for no schooling, some primary, and primary or higher was used as the MIV. SC: Scheduled Castes; ST: Scheduled Tribes; OBC: Other Backward Classes.

Appendix Table A8: OLS Estimates and Bounds for Effects of Secondary Schooling On Probability of Likely Being Depressed By Social Identity

		Control Mean	OLS	MTS+MTR+MIV
		(1)	(2)	(3)
A: Lower Secondary vs Primary				
China	Rural Hukou	0.38	-0.054*** (0.017)	[-0.09, 0.00] (-0.11, 0.00)
China	Urban Hukou	0.31	-0.076*** (0.025)	[-0.05, 0.00] (-0.06, 0.00)
India	Scheduled Tribe	0.17	-0.019 (0.020)	[-0.03, 0.00] (-0.06, 0.00)
India	Scheduled Caste	0.27	-0.014 (0.025)	[-0.004, -0.001] (-0.04, 0.00)
India	OBC	0.26	-0.012 (0.015)	[-0.02, 0.00] (-0.04, 0.00)
India	Muslim	0.23	0.035 (0.045)	[-0.03, 0.00] (-0.09, 0.00)
India	Hindu, other/no caste	0.25	-0.017 (0.017)	[-0.02, 0.00] (-0.03, 0.00)
B: Upper vs Lower Secondary				
China	Rural Hukou	0.32	-0.036 (0.026)	[-0.09, 0.00] (-0.12, 0.00)
China	Urban Hukou	0.24	-0.038 (0.025)	[-0.08, 0.00] (-0.10, 0.00)
India	Scheduled Tribe	0.15	0.006 (0.021)	[-0.02, 0.00] (-0.05, 0.00)
India	Scheduled Caste	0.25	-0.069*** (0.026)	[-0.09, 0.00] (-0.12, 0.00)
India	OBC	0.25	-0.035** (0.016)	[-0.05, 0.00] (-0.07, 0.00)
India	Muslim	0.26	-0.049 (0.045)	[-0.02, 0.00] (-0.08, 0.00)
India	Hindu, other/no caste	0.23	-0.023 (0.015)	[-0.03, 0.00] (-0.04, 0.00)
C: Post vs Upper Secondary				
China	Rural Hukou	0.29	-0.140*** (0.047)	[-0.20, 0.00] (-0.27, 0.00)
China	Urban Hukou	0.20	-0.052** (0.026)	[-0.08, 0.00] (-0.11, 0.00)
India	Scheduled Tribe	0.16	-0.047* (0.028)	[-0.03, 0.00] (-0.12, 0.00)
India	Scheduled Caste	0.18	-0.051 (0.033)	[-0.08, 0.00] (-0.23, 0.00)
India	OBC	0.21	-0.018 (0.018)	[-0.06, 0.00] (-0.09, 0.00)
India	Muslim	0.21	-0.049 (0.046)	[-0.12, 0.00] (-0.20, 0.00)
India	Hindu, other/no caste	0.21	-0.053*** (0.014)	[-0.08, 0.00] (-0.10, 0.00)
D: Upper Secondary vs Primary				

China	Rural Hukou	0.38	-0.091*** (0.025)	[-0.13, -0.03] (-0.16, -0.01)
China	Urban Hukou	0.31	-0.114*** (0.028)	[-0.08, -0.02] (-0.11, -0.01)
India	Scheduled Tribe	0.17	-0.014 (0.020)	[-0.03, 0.00] (-0.06, 0.00)
India	Scheduled Caste	0.27	-0.083*** (0.023)	[-0.08, 0.00] (-0.11, 0.00)
India	OBC	0.26	-0.047*** (0.014)	[-0.06, 0.00] (-0.08, 0.00)
India	Muslim	0.23	-0.014 (0.039)	[-0.07, 0.00] (-0.13, 0.00)
India	Hindu, other/no caste	0.25	-0.040*** (0.015)	[-0.03, 0.00] (-0.05, 0.00)

Notes: OLS estimates are from regressions of the depression indicator on dummy variables for the schooling comparisons. Robust standard errors in (.) in column 3.***p<0.01 **p<0.05 *p<0.10. In columns 4 estimated bounds are in [.] and corresponding 95% confidence intervals in (.) are from 999 bootstrap replications. Mothers' schooling with bins for no schooling, primary, and primary or higher used as the MIV. Country-specific sampling weights are applied to OLS regressions and estimated bounds.